Energy Research and Development Division

FINAL PROJECT REPORT

Smart Charging of Electric Vehicles and Driver Engagement for Demand Management and Participation in Electricity Markets

California Energy Commission

Edmund G. Brown Jr., Governor

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PREFACE

The California Energy Commission's Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solution, foster regional innovation and bring ideas from the lab to the marketplace. The California Energy Commission and the state's three largest investor-owned utilities – Pacific Gas and Electric Company, San Diego Gas & Electric Company and Southern California Edison Company – were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The Energy Commission is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

Smart Charging of Electric Vehicles and Driver Engagement for Demand Management and Participation in Electricity Markets is the final report for the Smart Charging of Electric Vehicles and Driver Engagement for Demand Management and Participation in Electricity Markets project (contract number EPC-14-057) conducted by Lawrence Berkeley National Laboratory. The information from this project contributes to the Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

This study collected electric demand, energy consumption, and activity data from March 2013 to February 2018 from 50 electric vehicle charging stations owned and operated by the Alameda County General Services Agency. Researchers analyzed each charging session to determine: (1) arrival and departure times; (2) duration of plug-in and charging; (3) total number of charging sessions; and (4) charging load flexibility. The analysis also covered the power pattern of the entire facility during this period and evaluated and quantified the effect of smart charging control systems on utility bills.

Based on this analysis, the researchers developed a set of smart charging frameworks to manage charging demand for fleet and non-fleet electric vehicles that use Alameda County's publicly available charging stations. For public electric vehicles, implementing these frameworks reduced the peak electricity demand during the peak time of 8 a.m. to 11 a.m. from 24.2 kilowatts (kW) to 10.0 kW. The aggregated charging power of all the public charging stations decreased by 12.0 kW, which was 26.7 percent of the original uncontrolled peak demand. For fleet electric vehicles, the smart charging frameworks reduced peak demand during the on- and mid-peak periods by 10.7 kW and 13.3 kW respectively in a week during the summer. For direct current fast charging vehicles, the maximum power reduction was 20 kW, which was nearly half of the direct current fast charging power in the normal mode. The median value of the power reductions was 4.3 kW, which is equal to the kW shed from one active charging session. Researchers also quantified the potential for the aggregated fleet of electric vehicles to participate in multiple demand response products in the California retail and wholesale electricity markets.

Keywords: electric vehicles, charging stations, charging behaviors, smart charging control, cost savings, load flexibility, load scheduling.

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EXECUTIVE SUMMARY

In January 2018, Governor Edmund G. Brown signed an executive order calling for 5 million zero emission vehicles on California's roads by 2030, along with 250,000 electric vehicle charging stations by 2025. The order represented a substantial increase from California's prior goal of 1.5 million zero-emission vehicles by 2025. The executive order states, "California is taking action to dramatically reduce carbon emissions from transportation – a sector that accounts for 50 percent of the state's greenhouse gas emissions and 80 percent of smog-forming pollutants."

Electric vehicles are key to helping California reach its ambitious climate change and air quality goals. Hybrid and electric vehicles continue to grow in popularity, with the Alliance of Automobile Manufacturers reporting that hybrid and electric vehicles represented 7.8 percent of California market share in 2018 compared to 3.6 percent in 2016. Fleet operators are also increasingly exploring electric vehicles as a way to reduce their environmental footprint while also keeping costs down.

Municipal and corporate fleets have the opportunity to use electric vehicles to reduce fuel costs and decrease greenhouse gas emissions. To minimize the costs of the electricity to charge their vehicles, fleet owners and public parking facility owners need to be able to manage charging based on electric vehicle usage to avoid electricity demand charges, leverage time-of-use electric rates, and participate in demand response programs and electricity markets.

The term "smart charging" refers to the intelligent charging of electric vehicles, where charging can be controlled and shifted based on grid loads according to the vehicle owner's needs. This helps to reduce electricity demand on the grid and thus lowers associated energy costs and utility bills for customers.

This project demonstrated that fleets and public parking facility owners can achieve cost savings in the near term and beyond with current electric vehicle and charging station technologies. In addition, simulation using real-world charging activity data collected in this study was used to demonstrate the potential for generating revenue through smart charging and participation in demand response and electric service markets.

Project Purpose

This project developed and demonstrated a charging control system, consisting of software and hardware, that was applied to over 40 Alameda County fleet electric vehicles and charging stations to monitor and control the scheduling and magnitude of charging power for each charging station port and electric vehicle pair. The system was used for County fleet vehicles and for several private electric vehicles whose owners volunteered to participate in the research. The researchers developed approaches to engage non-fleet electric vehicle owners who charge their vehicles at Alameda County's publicly available charging stations and manage their charging station loads to further reduce utility costs. These approaches can also be applied to commercial and workplace charging and provide large benefits in managing peak electricity demand across California by helping consumers reduce or shift their electricity use during times when electricity demand is high. Although the project focused on one-way (unidirectional) charging, the approach is compatible with future vehicles and chargers that may have two-way (bi-directional) charging capability.

During this study, there were 14 Level 1 and 36 Level 2 charging ports for public and fleet electric vehicles at the Alameda County parking garage, named AlCoPark. Level 1 charging stations use a normal 120-volt connection, which uses a standard household outlet, and charging times can be slow. Level 2 charging stations use a 240-volt power source, such as the one used for ovens or clothes dryers, and have much faster charging times than Level 1 chargers. In August 2017, a Level 3 direct current fast charging station, which can charge vehicles even more quickly, was installed on the street level for both public and fleet vehicles.

Since the installation of charging stations in March 2013, the number of charging sessions increased steadily to a rate of 200-250 per month by the end of 2014. During 2016, the number of charging sessions was around 400 per month. By 2017, the number of the charging sessions ranged from 600 to 900 each month and a few new charging stations had been installed.

The monthly peak electric demand of the entire facility increased to more than 140 kW compared to 80-90 kW before installation of the charging stations. Utility bills increased by $500-$600 in winter and $700-$1,000 in summer.

Project Process

The research had three main technical tasks:

- Task 1: Site and fleet characterization, data collection, and data analysis for control strategies.
- Task 2: Implement and demonstrate fleet and public electric vehicles' managed charging control system.
- Task 3: Quantify the potential of fleet and non-fleet electric vehicles in the managed charging control system as demand response capabilities in the retail and wholesale electricity markets.

During this demonstration project, the project partners worked together to achieve the goal of minimizing electricity costs related to electric vehicle charging. Alameda County provided significant support related to its fleet and public electric vehicle charging stations across the Bay Area, as well as information on customer need and feedback. The county tracked the operation of electric vehicle charging and the energy and demand patterns daily, especially after implementation of a set of smart charging control strategies. Prospect Silicon Valley recruited public electric vehicle drivers for the pilot study of charging control, prepared and circulated materials to drivers who frequently used the chargers at the garage, and worked with ChargePoint to help enroll participants into the study. Kisensum developed a dashboard for managing the fleet charging stations and the direct current fast charging station, and implemented the smart charging power control sequences from the Lawrence Berkeley National Laboratory server to the charging stations. ChargePoint provided significant technical support on the communication and control of charging stations, and created a dedicated group for the communication and control for the participants in the public charging pilot study with the research team.

At the beginning of the project, collection of charging session and meter data was initiated to enable analysis of charging behaviors at the AlCoPark Garage and in other facilities for multilocation smart charging control. The team calculated and analyzed metrics such as the monthly electricity demand before and after the use of the charging equipment, charging behaviors at the vehicle and charging station levels, and fleet electric vehicle trips and charging characterizations.

Using what was learned from the datasets, the team developed a set of smart charging control strategies for public electric vehicles, fleet electric vehicles, and the direct current fast charger. The researchers developed separate smart charging control platforms to meet the different requirements of each application. For public electric vehicles, researchers conducted several extensive end-to-end field tests to ensure that smart charging control did not affect drivers' mobility needs. The project demonstrated and evaluated smart charging control systems for Alameda County fleet electric vehicles from February 2017 to March 2018, and for public users at the AlCoPark Garage from August 2017 to November 2017. Offset of direct current fast charger load with demand management of fleet electric vehicle support equipment was demonstrated from September 2017 to March 2018. The County of Alameda has indicated that it intends to continue using the fleet and direct current fast charger smart charging systems after the completion of this project in March 2018 under a contract with Kisensum.

To address fleet EV charging, the project team developed an interface for monitoring and controlling the charging power of the charging stations for the fleet EVs at the AlCoPark garage. The charging status of all the charging stations for the fleet vehicles is displayed, and each station port is highlighted with a color indicating its status. In addition, a user can pause charging or override the scheduled charging of any station port. Fleet operators can make several selections to schedule, postpone, or stop a charging session.

The public station charging control system required engagement of the EV drivers. The project team configured a physical server located at Lawrence Berkeley National Lab with several software programs written or applied in this project that included: (1) interface with a web-based text messaging service to communicate directly with public station users; (2) web-page forms for receiving anticipated session end times and charging energy needs from public station users; (3) a database to store anonymized charging station data; and (4) a smart charging optimization code for creating cost-minimizing charging schedules that met drivers' needs. As with the fleet charging control, software created in this project that was located on the Kisensum server communicated to the public charging stations via the ChargePoint API, the charging station, the charging station vendor, and the charging power controller and optimizer.

To reduce electric utility demand charges related to direct current fast charging sessions, a control strategy reducing the charging power of concurrent fleet Level 2 charging sessions was implemented.

Project Results, Challenges, and Lessons Learned

The more noteworthy project results include:

- Developed the smart charging control system platforms for public and fleet electric vehicles and the direct current fast charger.
- Recruited frequent public charging users at the AlCoPark parking garage to participate in the pilot study and demonstrated public electric vehicle managed charging to achieve utility bill savings by managing peak demand.
- Quantified the potential of the fleet electric vehicle managed charging control system for multiple demand response products in the California retail and wholesale electricity markets.

In 2017, smart charging control strategies for fleet and direct current fast chargers were implemented in February and August independently. The primary period for public smart charging was from August to October. The total cost savings in 2017 were $2,651 which included $1,697 for fleet vehicles, $169 for public vehicles, and $785 for direct current fast chargers.

Over the period of smart charging demonstration in 2017, the AlCoPark Garage electric utility costs did not increase as much as would be expected given the increasing number of charging sessions. This was a result of the implementation of the smart charging control system and the newly installed direct current fast charging station in August of that year.

Fleet Electric Vehicles

In 2017, nearly 1,000 charging sessions were controlled to minimize the peak demand of fleet electric vehicles, representing about 25 percent of total fleet charging sessions. The average cost saving was about $1.80 per session. In one week during the summer, the peak demand during the on- and mid-peak periods was reduced by 10.7 kW and 13.3 kW, respectively.

The charging behavior indicated that most fleet electric vehicles return to be charged during on-peak hours, leading to very high demand charges (charges based on a commercial or industrial customer's peak electricity use that are paid on top of the actual cost of the electricity). With controlling only 25 percent of the fleet charging session, the smart charging control reduced 44.3 percent of the original on-peak demand without any effect on the use of fleet vehicles the following day.

Challenges included having more fleet plug-in vehicles than chargers, which limited the cost saving potential from the smart charging control. In addition, fleet staff could not rotate vehicles to available chargers outside of garage operating hours (7 a.m. to 7 p.m.). Simple scheduling works well for fleet charging, but may vary depending on patterns of fleet vehicle activity. Given the current limitations, a better coordinated fleet charging system would improve the performance (that is, lower utility costs) by linking fleet vehicle trip management with the smart charging control. Moreover, the fleet electric vehicle dashboard (a web-based user interface displaying AlCoPark charging station status and enabling control) could be fully used to improve the fleet charging control.

Public Electric Vehicles

For the pilot study participants, use of the charging controls reduced the daily peak demand by 7.0 kW. During the original peak period from 8 a.m. to 11 a.m., peak demand was reduced from 24.2 kW to 10.0 kW. The total charging power of all the public charging stations decreased by 12.0 kW, about 26.7 percent of the original uncontrolled peak electric vehicle charging demand.

For the public charging control system, only about five percent of all public charging sessions were controlled during the pilot study period. Public drivers need educational opportunities, such as flyers and workshops, to make them aware of the effect of smart charging control on utility costs and the environment. In addition, customers' request for charging must be guaranteed by the end of the charging session without any compromise of the charging request.

Difficulties were encountered in recruiting and maintaining volunteers for study participation. Future studies of a similar nature would benefit from more knowledge and information on incentivizing human behavior with respect to public participation recruitment and retention.

Direct Current Fast Charger

For Direct Current Fast Charger sessions, the maximum power reduction was 20 kW, which was nearly half of its charging power in the normal mode. The median value of the power reduction was 4.3 kW.

Due to their relatively high power, about 50 kW compared to about 7 kW for Level 2 charging, Direct Current Fast Charger can contribute to substantial electric utility energy and demand charges, especially during on-peak periods of time-of-use rates. The approach developed and demonstrated in this study, reduced the charging power on selected fleet charging stations during Direct Current Fast Charger sessions. Such a short period of limiting charging power would not have much effect on the charging sessions of fleet vehicles, because fleet vehicles are usually charged in the garage over long periods and often overnight. The performance of this control strategy for managing the power demand from a Direct Current Fast Charger session in a short period varies along with the number of active fleet charging sessions. Each active charging session can contribute about 4.5 kW of power reduction to offset the DCFC demand.

Electric Market Participation

Flexibility in scheduling the charging of individual fleet EVs leads to greater revenue in all demand response and electric grid market participation. For example, monthly regulation revenue was approximately doubled when the fleet EV charging baseline was controlled rather than uncontrolled. One of the most critical aspects of smart charging control is the ratio of the time an EV is connected to a charging station port and the time the EV is actively charging. The simulations performed in this study show that the ratio does not have to exceed roughly 2-3 to maximize revenue from regulation ancillary services market participation. This is a good finding for EV fleet owners or aggregators since it means that, with regards to maximizing regulation revenue, participating EVs do not have to be left connected to charging stations for very long periods after charging is complete, which will allow a greater utilization of charging equipment. Wholesale demand response and ancillary services markets have minimum levels of participation. This study shows that, for the EV fleet simulated, any threshold below 40 kW corresponds to maximum market participation revenues. Either threshold requirements have to be kept low or larger aggregations of fleet EVs will be needed for profitable market participation with higher thresholds.

Technology Transfer

This project successfully demonstrated a set of smart charging strategies at an Alameda County public parking garage, that also houses the county's primary fleet vehicle facility, to manage charging station loads and reduce utility costs. Alameda County was so pleased with the outcomes of the project that they paid a two-year contract to continue operation of the fleet management smart charging system at the AlcoPark Garage. Another significant success of this project comes in the form of technology transfer where a major charging service provider, ChargePoint, purchased project partner Kisensum in order to incorporate the technology developed in this project into their commercial product offerings because of the value that it brings to their fleet and commercial customers.

Benefits to California

The new smart charging optimization algorithms and charging control systems that were developed and demonstrated in this project, along with the acquired knowledge of charging behaviors, will help increase the use of commercial charging stations in California which will, in turn, provide cost savings for customers and load aggregators, and reduce greenhouse gas emissions. As a result of this project, LBNL was able to further build out a tool to help fleet owners incorporate PEVs into their fleets. LBNL is working with Alameda, Oakland, and Caltrans to help facilitate PEV smart charging technologies into their large-scale fleet procurement processes.

CHAPTER 1: Introduction

Increased numbers of electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) in California's new vehicle market has the potential to substantially reduce air pollution, carbon emissions, and the consumption of carbon fuels. To combat climate change, the California has implemented state and private sector actions to accelerate electric vehicle adoption.

California has a goal of 5 million zero emission vehicles (ZEVs) on the roads by 2030 and 250,000 EV charging stations by 2025. As of November 2018, more than 500,000 EVs have been sold in California, according to tracking by Veloz, a public-private coalition of major EV industry stakeholders. According to the California Public Utility Commission, more than 18,000 light-duty EV charging plugs are available throughout the state. Local governments, together with vehicle manufacturers, electric utilities, electric vehicle charging companies, and states, have launched electric vehicle fleet projects to showcase electric vehicles in multiple government fleets (USDOE, n.d.).

The Smart Charging of Electric Vehicles and Driver Engagement for Demand Management and Participation in Electricity Markets project creates substantial direct emission reductions, and serves as a model to scale this clean energy solution nationwide. Funded through the Federal Highway Administration's Congestion Mitigation and Air Quality Improvement Program, the Local Government Electric Vehicle Demonstration Project is an initiative to test the utility and benefits of using electric vehicles in municipal fleet operations.[1] The project in the San Francisco Bay Area is supported by the Metropolitan Transportation Commission and is a partnership between Alameda County, Sonoma County, Sonoma Water District, Transportation Authority of Marin, City of San Francisco, City of San Jose, City of Fremont, City of Concord, City of Oakland, City of Santa Rosa, and the Bay Area Climate Collaborative. About 90 all-electric vehicles and 90 charging points are installed throughout the Bay Area.

Commercial, e.g. fleet, public, workplace, EV charging is provided by Level 2 or DCFC equipment at power levels of approximately 7 kW and 50 kW, respectively. With EVs likely making up the vast majority of the five million ZEVs targeted to be operating in California by 2030, the aggregate charging demand will put considerable strain on the electric grid. The implementation of smart charging controls can mitigate this strain by enabling aggregations of EV charging stations to participate in wholesale or retail demand response programs or wholesale ancillary services markets. Demand response programs typically work by sending a signal for participants to lower demand during particular periods and smart charging can receive these signals and decrease EV charging demand for those EVs that are able to participate without compromising their ability to provide transit. Ancillary services provided by batteries typically balance differences between electric supply and demand on very short time

[1] For more information, see http://www.acgov.org/sustain/next/evp.htm.

scales by consuming (charging) or providing (discharging) power. Smart charging of aggregations of uni-directional charge only EVs can schedule and control the amount of ancillary service they can provide by charging at a level lower than the charging station's peak power and increasing or decreasing charging power. For commercial ratepayers that are most likely on time of use rates where electric consumption and peak demand costs vary depending on time of day, EV charging increases costs primarily because of the increased peak demand that it creates. Smart charging controls lower ratepayer costs by minimizing peak demand by spreading demand over longer periods or shifting demand to lower cost periods.

The project developed and demonstrated a scalable managed charging control approach that reduced operating costs related to EV charging. Lower operating costs were obtained by controlling EV charging for demand charge mitigation and by taking advantage of time-of-use rates. Simulation and data analysis using actual public and fleet EV charging data demonstrated potential revenues from managing charging to provide grid services. The project demonstrated managed charging on both fleet and privately owned EVs. Alameda County provided nearly 50 fleet EVs for this project, with drivers of privately owned vehicles that charge at Alameda County charging stations also engaged in the project. By developing scalable managed charging solutions for fleet operators and personal vehicle owners, this project developed and demonstrated a managed charging control approach that can be used for commercial, workplace, and home charging throughout California to provide benefits in managing peak demands and offering valuable grid services.

Recent studies on the adaptation needs of the existing operational control mechanisms to achieve smart charging often propose novel planning and control approaches. These approaches can be categorized into direct and indirect control approaches (Galus, Vayá, Krause, & Andersson, 2013). In direct control approaches, the control actions are attained without the vehicle owner in the control loop. Often, load aggregations are created to increase the size of the resource so it can offer economic benefits to the aggregator (Guille & Gross, 2009). In (Sanchez-Martin, Sanchez, & Morales-Espana, 2012), for example, the authors proposed a direct load control strategy to provide grid services for three different predefined mobility patterns. In (Su & Chow, 2012), the authors conducted a simulation study for 3,000 EVs parked at a municipal parking lot and evaluated the real-time performance of a direct control approach, which maximizes the expected state of charge of the EV aggregation in the next time step subject to mobility constraints. In (He, Venkatesh, & Guan, 2012), the authors develop an optimal direct control scheme based on global charging costs. The authors compare the proposed direct control scheme to the local scheduler in a simulation environment including 100–400 EVs. The arrival times of the EVs, the charging periods, and the initial energies of EVs are assumed to have a uniform distribution, which is unrealistic in practical implementations.

In indirect control approaches, the electric vehicle owner manages the control authority through a decentralized strategy. These strategies often make use of a broadcasted exogenous price signal. The cost of energy is minimized at each electric vehicle charging station considering the local mobility and charging constraints. An iterative cost minimal charging framework based on game theory is presented in (Ma, Callaway, & Hiskens, 2013) and a similar strategy is given in (Gan, Topcu, & Low, 2013). Additionally, EV charging problem is modeled as convex optimization problem, with proof of the existence of optimal solution. However, these approaches do not include the impacts or additional costs that can be induced on the distribution network due to increased demand during low cost periods and often assume that the supply and non-EV demand is known.

Many researchers have investigated the benefits of EV charging and different grid-level services that can be provided by an aggregation of EV population using different control approaches. Note that various services can be provided by EVs and many studies have quantified the benefits of smart charging from various stakeholder perspectives (Rotering & Ilic, 2011). In (Rotering & Ilic, 2011), the authors estimate that smart charging will reduce the daily electricity costs of a plug-in hybrid EV by $0.23. They also identify daily profits for the individual driver when the charging of the vehicles can be regulated. The economic benefits of fleets that participate in specific markets have also been extensively studied. In (Finn, Fitzpatrick, & Connolly, 2012), the authors use historical market data and charging data collected from a EV located in a residential household to investigate financial savings and peak demand reduction. The authors conclude that the peak EV demand can be reduced by up to 56 percent.

A previous study by Lawrence Berkeley National Laboratory (LBNL) analyzed the EV charging load of commercial charging stations located in Pacific Gas and Electric's service territory and evaluated various smart charging control approaches assuming perfect knowledge of charging session start times, end times, and energy delivered (Kara et al., 2015). The project presented in this report built upon the algorithms developed in the earlier study and modified them to minimize fleet and public EV charging costs with session activity that could actually be acquired.

In this project, LBNL proposed a set of smart charging control strategies and developed each smart charging control system for fleet EVs, public EVs, and direct current fast charging by analyzing the charging behavior and power pattern of each group of EVs. Especially for public EVs, LBNL modified the charging control algorithm based on the actual charging requirements and conducted many field tests before the implementation. In addition, LBNL quantified the potential of the aggregated fleet EVs to participate in multiple demand response products in the California retail and wholesale electricity markets.

CHAPTER 2:
Demonstration Site Overview

Alameda County is a partner in the Local Government Electric Vehicle Fleet Project, an initiative to showcase electric vehicles in multiple government fleets. By April 2013, the county had purchased and installed 40 EV charging stations, including 22 charging stations in Alameda County's parking garage, the AlCoPark Garage. In 2017, the county installed three new EV charging stations and one direct current fast charging (DCFC) station in the garage.

At the AlCoPark Garage, there were three types of EV charging station applications: (1) public charging stations for privately owned and fleet vehicles; (2) charging stations for only fleet vehicles, located in a restricted access area; and (3) a DCFC station for privately owned and fleet vehicles. There were 14 Level 1 stations (up to 1.6 kilowatt [kW] charging rate), 36 Level 2 stations (up to 6.6 kW charging rate), and one DCFC station (up to 50 kW charging rate) at the AlCoPark Garage during 2017, the primary demonstration period of this study (Figure 1).

Figure 1: AlCoPark Garage Electric Vehicle Charging Stations

Source: Lawrence Berkeley National Laboratory and ChargePoint

Public access to the public charging stations was only available during garage operating hours, 7:00 a.m. to 7:00 p.m., seven days a week. However, fleet operators could charge fleet EVs on those stations at any time. Fleet operations had typical business hours of 7:00 a.m. to 7:00 p.m.

and could leave EVs to charge overnight on either public or fleet stations. The DCFC station went into operation in August 2017 and was accessible 24-hours seven days per week.

Table 1 lists the location and number of each type of EV charging station at AlCoPark Garage.

Table 1: Installed Charging Stations in the AlCoPark Garage

Location	Charging Stations	Number	Ports
Basement	CT2100	4	Each with a L1 and L2 port
	CT4020	8	Each with two L2 ports
2nd Floor	CT2100	5	Each with a L1 and L2 port
	CT4020	3	Each with two L2 ports
8th Floor	CT2100	5	Each with a L1 and L2 port
Street Level	CPE200 DCFC	1	1 SAE Combo and 1 CHAdeMO

Source: Lawrence Berkeley National Laboratory

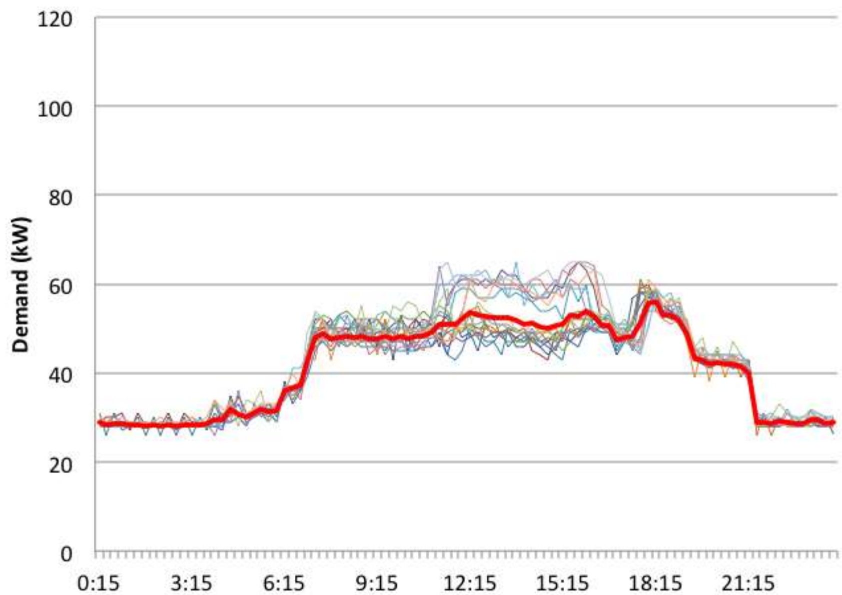
The Alameda County vehicle fleet facility is located in the basement of the AlCoPark Garage. In 2017, the fleet consisted of 33 EVs and 7 plug-in-hybrid electric vehicles (PHEVs) (Figure 2).

Figure 2: Alameda County Fleet Electric Vehicles and Plug-in Hybrid Electric Vehicles Dispatched from AlCoPark Garage

Source: Lawrence Berkeley National Laboratory, Nissan, General Motors, Ford, and Toyota

Alameda County was motivated to implement smart charging due to the increased cost of electricity observed after implementing EVs and EV charging at the AlCoPark Garage facility. Figure 3 shows the daily and monthly average electricity demand (red line) at the facility in February 2013 before EV and EV charging was implemented.

Figure 3: Daily Demand Profiles for AlCoPark Garage in February 2013 before Electric Vehicle Charging

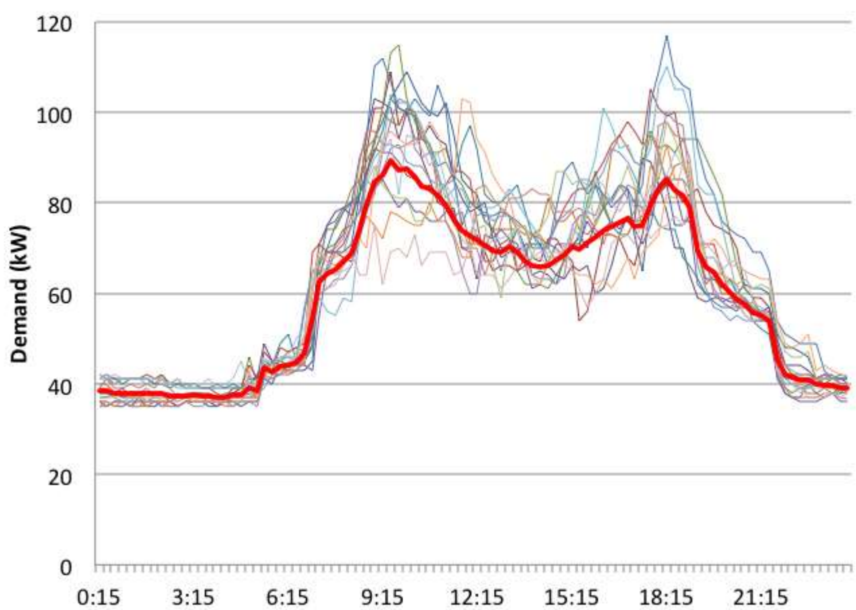


Red line is monthly average.

Source: Lawrence Berkeley National Laboratory

After EV charging was implemented at the AlCoPark Garage for both public and fleet EVs, but before installation of the DCFC station, peak monthly electricity demand increased substantially from ~65 kW to ~115 kW (see Figure 4).

Figure 4: Daily Demand Profiles for AlCoPark Garage in February 2015 after Electric Vehicle Charging



Red line is monthly average)

Source: Lawrence Berkeley National Laboratory

This corresponds to an increase of roughly $700 per winter month (November-April) and $1,500 per summer month (May-October) in electric utility demand charges alone. The primary objective of developing automated smart charging control systems in this research project was to reduce the demand peaks caused by EV charging.

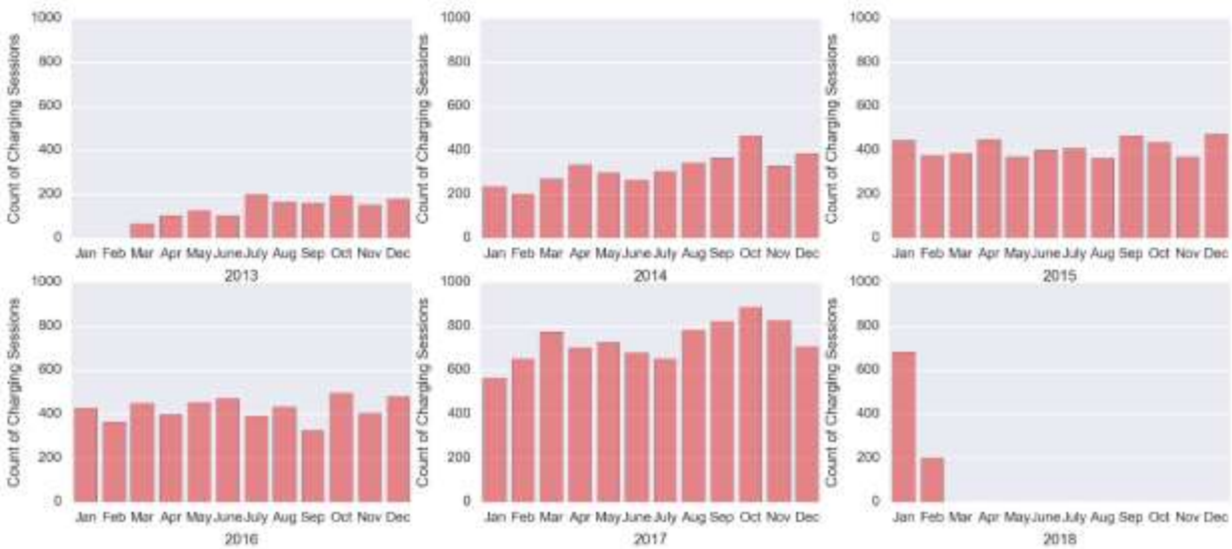
Electric Vehicle Charging Behaviors and Facility Power Usage

EV charging behaviors at the AlCoPark Garage charging stations are characterized using the following metrics: (1) arrival and departure times; (2) plug-in and charging durations; (3) number of charging sessions; and (4) charging load flexibility.

Charging Behaviors

Since installation of charging stations in March 2013, the number of charging sessions had increased to a fairly steady rate of 200-250 per month by the end of 2014 (Figure 5). In 2017, the number of the total charging sessions ranged from 600 to 900 each month despite there being only a few new charging stations installed, indicating more EVs were charging at the site.

Figure 5: Monthly Totals of Charging Sessions, March 2013-February 2018



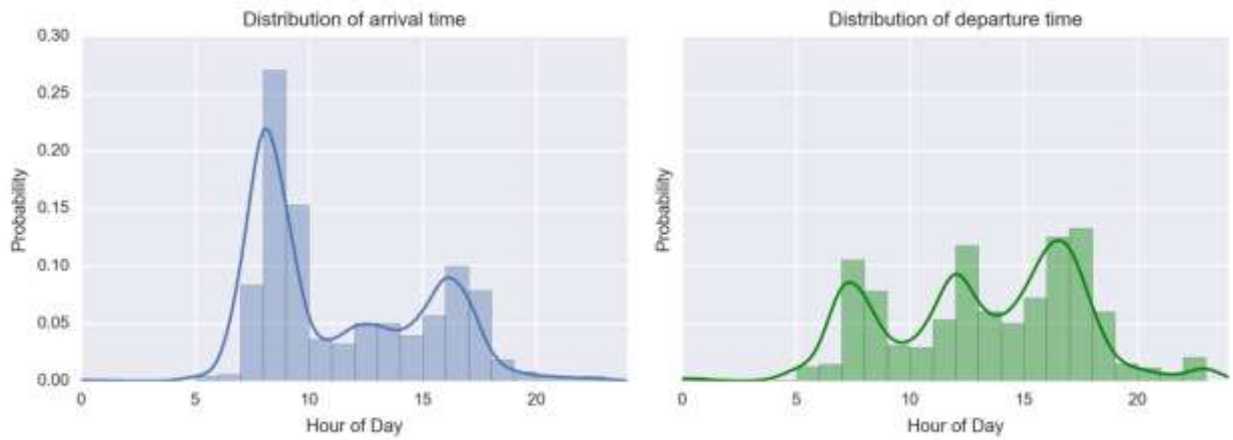
Source: Lawrence Berkeley National Laboratory

Alameda County fleet EV managers primarily use the designated basement (known as "AlcoBase") charging stations to charge the fleet EVs. They also move and shift fleet EVs around all charging stations to fully charge EVs for the next day's use. Figure 6 shows the distribution of arrival and departure times for sessions at the public charging stations and the designated AlcoBase charging stations separately, with a likely normal distribution of charging behavior at the public charging stations for privately owned vehicles. About half of privately owned vehicles arrive at the charging stations before 10 a.m.

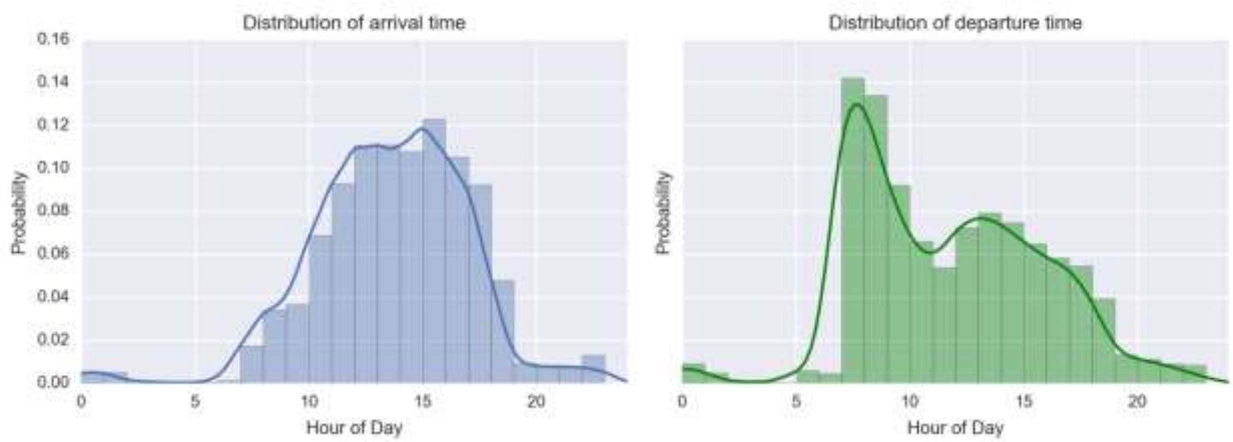
Given the charging time limit at Level 1 and 2 stations, some vehicles unplug during the noon hour while others leave the garage in late afternoon. As illustrated in Figure 6, fleet vehicles typically leave the garage in the early morning. The arrival times suggest that charging of fleet vehicles starts anywhere from early morning to late afternoon, which coincides with the typical working hours of a non-residential location (that is, a commercial parking garage).

Figure 6: Distribution of Arrival Time and Departure Time of Charging Sessions at (a) Public Charging Stations and (b) Fleet Charging Stations

(a) Sessions at the Public Charging Stations



(b) Sessions at Fleet Charging Stations from March/2013 to February/2018



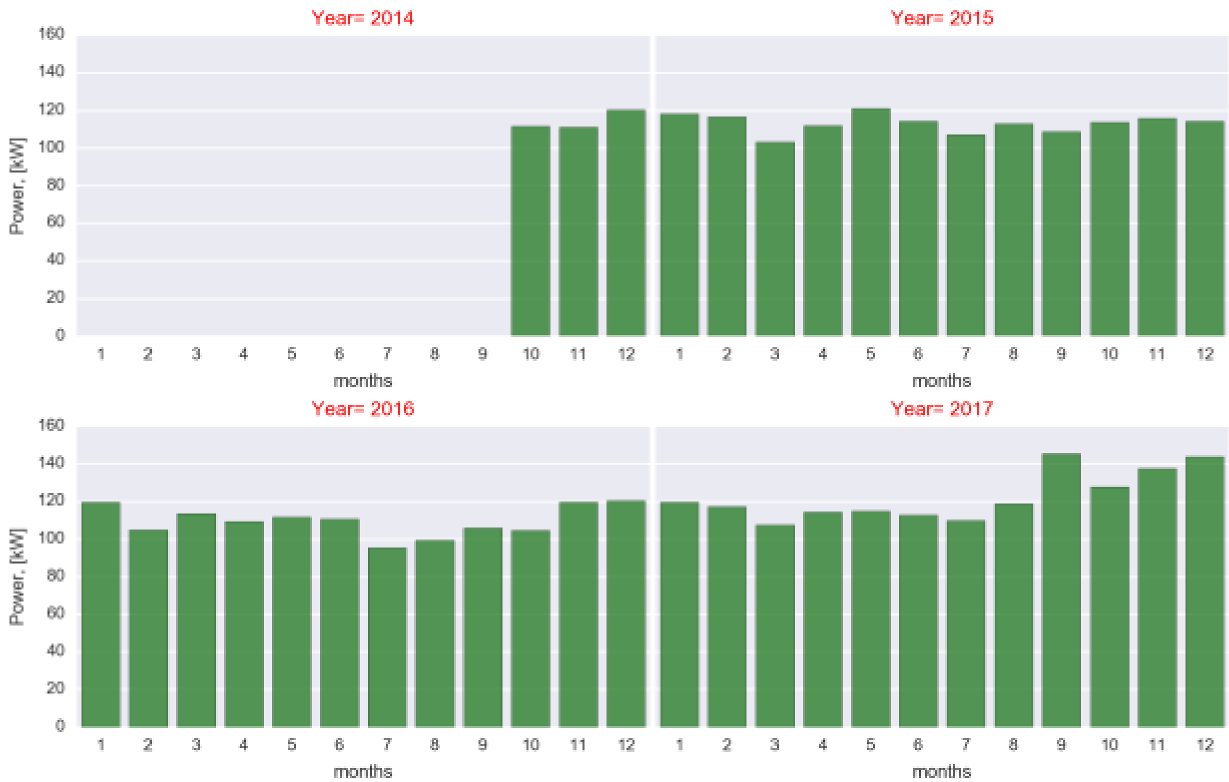
Source: Lawrence Berkeley National Laboratory

Facility Power Usage

The researchers observed that the number of EV charging sessions increased substantially from about 400 per month to more than 600 per month since February 2017 (Figure 7). While that increase suggests the facility's peak power demand would increase as well, implementation of the smart control strategy to manage the fleet charging stations in fact reduced demand by about 10 kW despite the number of EV charging sessions rising to nearly 800 in March 2017.

In addition, the facility installed a new DCFC charging station by the end of August 2017, which explains a sudden rise of monthly peak demand by 26 kW in September 2017. Again, the number of EV charging sessions increased to nearly 900 in October 2017, and the monthly peak demand decreased significantly by 18 kW. LBNL implemented the smart charging control strategy for a few privately owned vehicles and the DCFC charging station separately from late August 2017.

Figure 7: Monthly Peak Power Demand of AlCoPark Garage from October 2014-December 2017

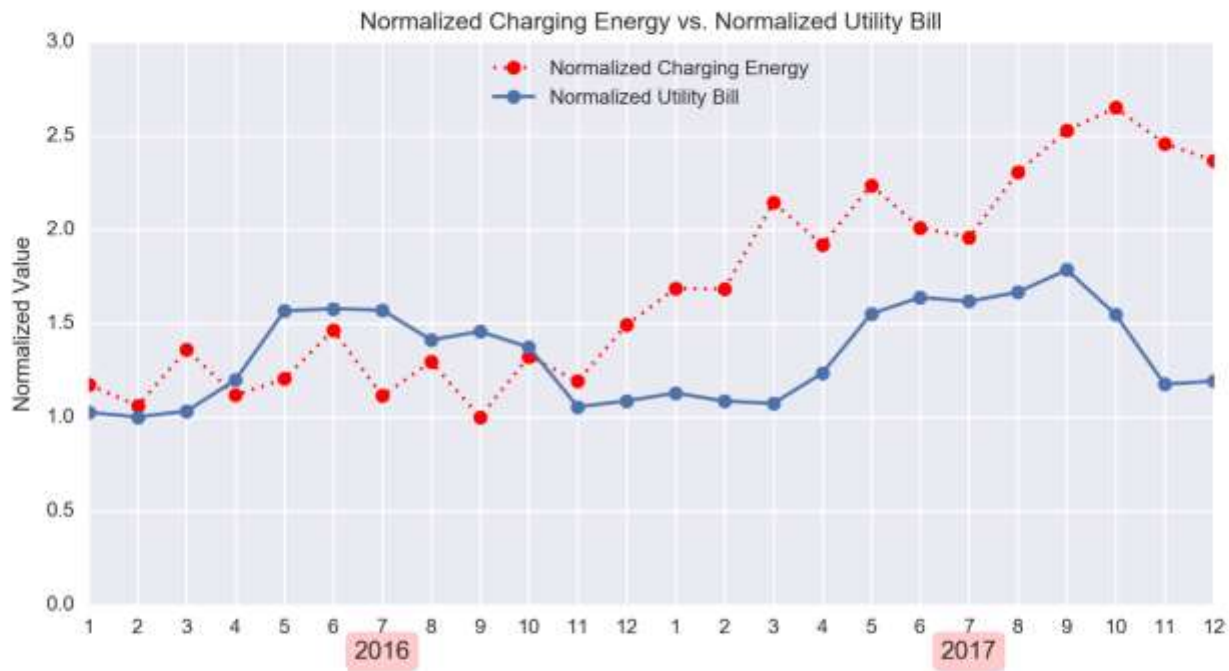


Source: Lawrence Berkeley National Laboratory

Electric Vehicle Charging Energy Use and Utility Bills

The increase in the number of charging sessions leads to the increase of the charging energy associated with the facility's electric utility bills. Figure 8 shows the normalized monthly EV charging energy usage and the normalized monthly facility utility bill in 2016 and 2017. Notice that the monthly EV charging energy use increased considerably by the end of 2017, more than 2.5 times the energy use in 2016. However, the monthly facility utility bills did not increase as much as the EV charging energy usage because (1) the cost of EV charging only represented about 10 percent of the facility's monthly utility bill; and (2) a set of smart charging control strategies were implemented for reducing the peak demand and energy charges since February 2017.

Figure 8: Electric Vehicle Charging Energy Use and Utility Bills in 2016 and 2017



Source: Lawrence Berkeley National Laboratory

CHAPTER 3:
Smart Charging Methods

The AlCoPark garage is in Pacific Gas and Electric Company's (PG&E) E-19 time-of-use (TOU) service rate (PG&E, 2010) shown in Table 2. This rate plan is suitable for customers who can be flexible with their power use between the maximum peak, maximum part-peak, and off-peak periods. The utility averages electric demand over 15-minute periods to determine peak values in each monthly billing period type. Typically, the cost associated with the demand charge accounts for about half of the total electric cost for non-residential facilities. Shifting demand for charging from one period to another can provide cost savings. For example, a customer could save $114 by shifting the demand of a single 6.6 kW Level 2 charging session from the billed maximum demand period to an off-peak period in a summer month (May 1 to October 31; winter is November 1 to April 30).

Table 2: Pacific Gas and Electric Company E-19 Rate Schedule

Demand Charges	$/kW	Time Period
Maximum Peak Demand Summer	$18.74	12:00 p.m.-6:00 p.m.
Maximum Part-Peak Demand Summer	$5.23	8:30 a.m.-12:00 p.m. and 6:00 p.m.-9:30 p.m.
Maximum Demand Summer	$17.33	Any time
Maximum Part-Peak Demand Winter	$0.13	8:30 a.m.-9:30 p.m.
Maximum Demand Winter	$17.33	Any time
Energy Charges	**$/kW**	**Time Period**
Peak Summer	$0.14726	12:00 p.m.-6:00 p.m.
Part-Peak Summer	$0.10714	8:30 a.m.-12:00 p.m. and 6:00 p.m.-9:30 p.m.
Off-Peak Summer	$0.08057	Any time
Part-Peak Winter	$0.10166	8:30 a.m.-9:30 p.m.
Off-Peak Winter	$0.08717	Any time

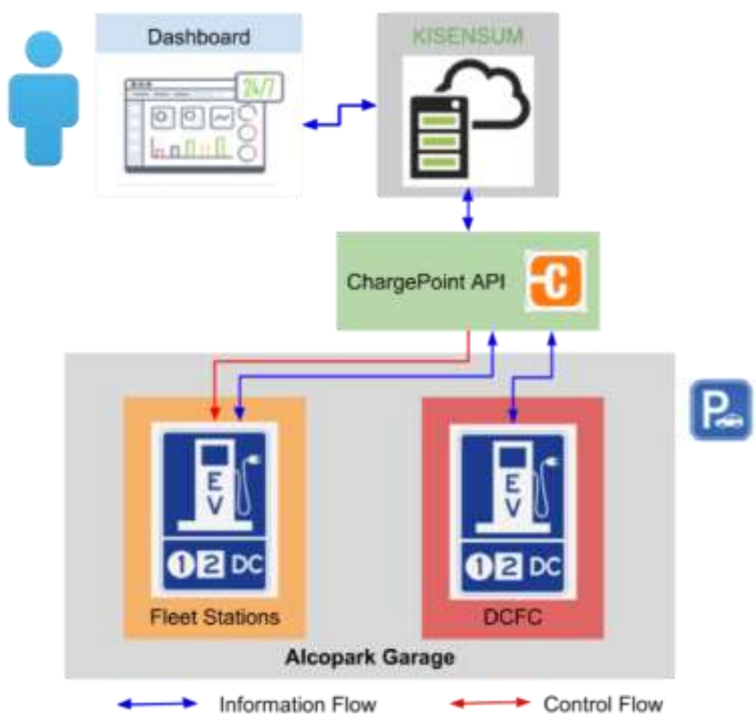
Source: Pacific Gas and Electric Company, 2016

The AlcoPark Garage is on the peak day pricing rate, which provides customers the opportunity to manage their electric costs by reducing load during high-cost periods or shifting load from high-cost periods to lower-cost periods. There are 9-15 peak day pricing event days per year. On event days, the utility adds a surcharge between 2:00 pm and 6:00 pm, which is $1.20/kWh for E-19 tariff rate.

Smart Charging Strategies and Approaches

The researchers configured smart charging control systems for EVs charging at fleet, public, and DCFC stations. Figure 9 shows a schematic of the system architecture for fleet charging. A cloud-based server configured and managed by project team member Kisensum ran software created for this project that communicated with the fleet charging stations, including the DCFC station, via the ChargePoint application program interface (API). Kisensum also created a web-based dashboard (Figure 10) that fleet staff could access through any web browser to monitor and manage fleet EV charging. The dashboard interface sent fleet charging schedules and charging set points to the fleet charging stations.

Figure 9: System Architecture for Smart Charging Control of Fleet Charging Stations



Source: Lawrence Berkeley National Laboratory

Fleet Smart Charging Strategy and Approach

Over the course of this project, approximately 40 fleet EVs were dispatched during weekdays from the AlCoPark Garage coordinated by the Alameda County fleet management staff. With few exceptions, all fleet EVs were parked in the garage each night of the study. The overnight parking provided sufficient time for each fleet EV to charge fully using a Level 2 charger. This charging behavior provided flexibility to manage the charging start time and power level to shift charging from on- and mid-peak periods (12 p.m. to 6 p.m. and 6 p.m. to 9:30 p.m., respectively) to the off-peak period (9:30 p.m. to 8:30 a.m.). Fleet EVs typically left the garage in the morning and returned to the garage in the afternoon. Fleet management staff would often immediately plug a returning EV into a fleet charging station. With fewer charging station ports than EVs, fleet staff would rotate EVs to ports as they became available.

The aggregated energy demand to charge the returned fleet EVs often resulted in high demand charges during the on-peak period. To minimize the charging power demand during peak hours, a set of charging control strategies for fleet vehicles was implemented that scheduled the availability of fleet charging stations. Charging stations for fleet EVs were grouped into staged schedules with start times of 9:30 p.m., 11:30 p.m., 1:30 a.m., and 3:30 a.m. As a result, the charging power demand of fleet vehicles was allocated to off-peak hours in different stages. Meanwhile, the aggregate charging power can be reduced significantly.

Kisensum developed an interface for monitoring and controlling the charging power of the charging stations for the fleet EVs at the AlCoPark garage (Figure 10). The charging status of all the charging stations for the fleet vehicles is displayed, and each station port is highlighted with a color indicating its status (for example, red indicates active charging). In addition, a user can pause charging or override the scheduled charging of any station port. The last column labeled "Action" with the control option "Defer Now" allows users to postpone a charging session. The option "Sched" refers to the charging control using the user-defined demand reduction schedule. During the scheduled period, the charging port power setting is scheduled to the Level 1 charging level, which is about 1.5 kW. Other than that, the charging power will be reset to normal, which is about 6.6 kW.

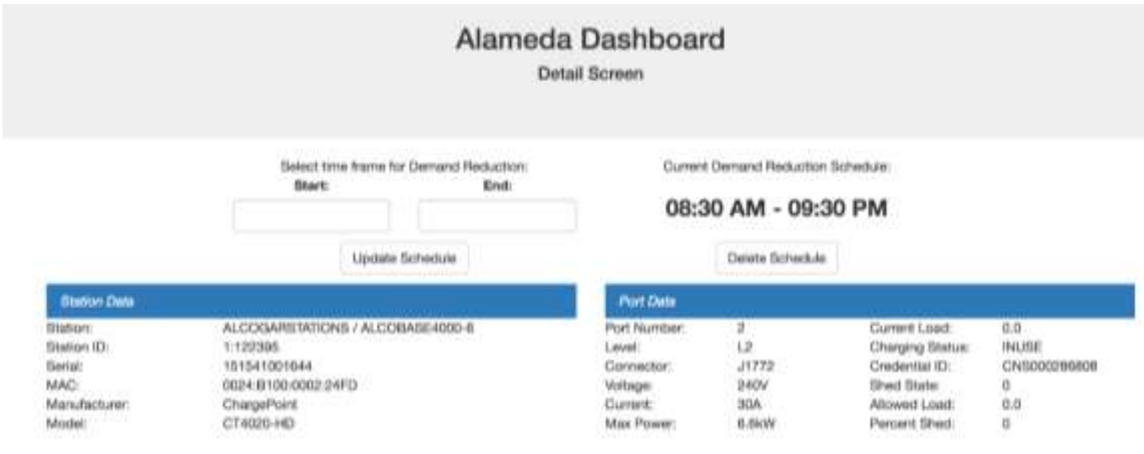
Figure 10: Smart Charging Control System Dashboard for Fleet Electric Vehicles and Direct Current Fast Charger

Station Name	Vehicle	Load	Status	Demand Reduction Schedule	Action
AlcoBase CT4000					
ALCOBASE4000-1, Port 1	N/A	0	AVAILABLE	08:30:00 - 23:30:00	Defer Now Sched Detail
ALCOBASE4000-1, Port 2	N/A	0	AVAILABLE	08:30:00 - 01:30:00	Defer Now Sched Detail
ALCOBASE4000-2, Port 1	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE4000-2, Port 2	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE4000-3, Port 1	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE4000-3, Port 2	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE4000-4, Port 1	3330 Leaf 2016	5.971	INUSE	None	Defer Now Sched Detail
ALCOBASE4000-4, Port 2	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE4000-5, Port 1	N/A	0	AVAILABLE	08:30:00 - 21:30:00	Defer Now Sched Detail
ALCOBASE4000-5, Port 2	N/A	0	INUSE	08:30:00 - 03:30:00	Defer Now Sched Detail
ALCOBASE4000-6, Port 1	N/A	0	AVAILABLE	08:30:00 - 03:30:00	Defer Now Sched Detail
ALCOBASE4000-6, Port 2	N/A	0	AVAILABLE	08:30:00 - 21:30:00	Defer Now Sched Detail
ALCOBASE4000-7, Port 1	N/A	0	AVAILABLE	08:30:00 - 23:30:00	Defer Now Sched Detail
ALCOBASE4000-7, Port 2	N/A	0	AVAILABLE	08:30:00 - 01:30:00	Defer Now Sched Detail
ALCOBASE4000-8, Port 1	Fleet Master	0	INUSE	08:30:00 - 23:30:00	Defer Now Sched Detail
ALCOBASE4000-8, Port 2	N/A	0	AVAILABLE	08:30:00 - 01:30:00	Defer Now Sched Detail
AlcoPark Basement					
ALCOBASE - 001, Port 1	N/A	0	UNREACHABLE	None	Defer Now Sched Detail
ALCOBASE - 001, Port 2	2943 Focus Pool 20 Silver 2012	5.881	INUSE	None	Defer Now Sched Detail
ALCOBASE - 002, Port 1	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE - 002, Port 2	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE - 003, Port 1	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE - 003, Port 2	N/A	5.984	INUSE	None	Defer Now Sched Detail
ALCOBASE - 004, Port 1	N/A	0	AVAILABLE	None	Defer Now Sched Detail
ALCOBASE - 004, Port 2	3199 Focus EV pool 20	5.904	INUSE	None	Defer Now Sched Detail
Alco DC Fast					
FAST CHARGER, Port 1	N/A	0	AVAILABLE	None	Defer Now Sched Detail

Source: Lawrence Berkeley National Laboratory

When clicking the “Detail” option, a new popup page (Figure 11) allows the user to set a new demand reduction schedule or update an existing schedule. Again, during the demand reduction schedule, the vehicle will not charge unless overridden.

Figure 11: Smart Charging Control System Dashboard for Fleet Electric Vehicles and Direct Current Fast Charger



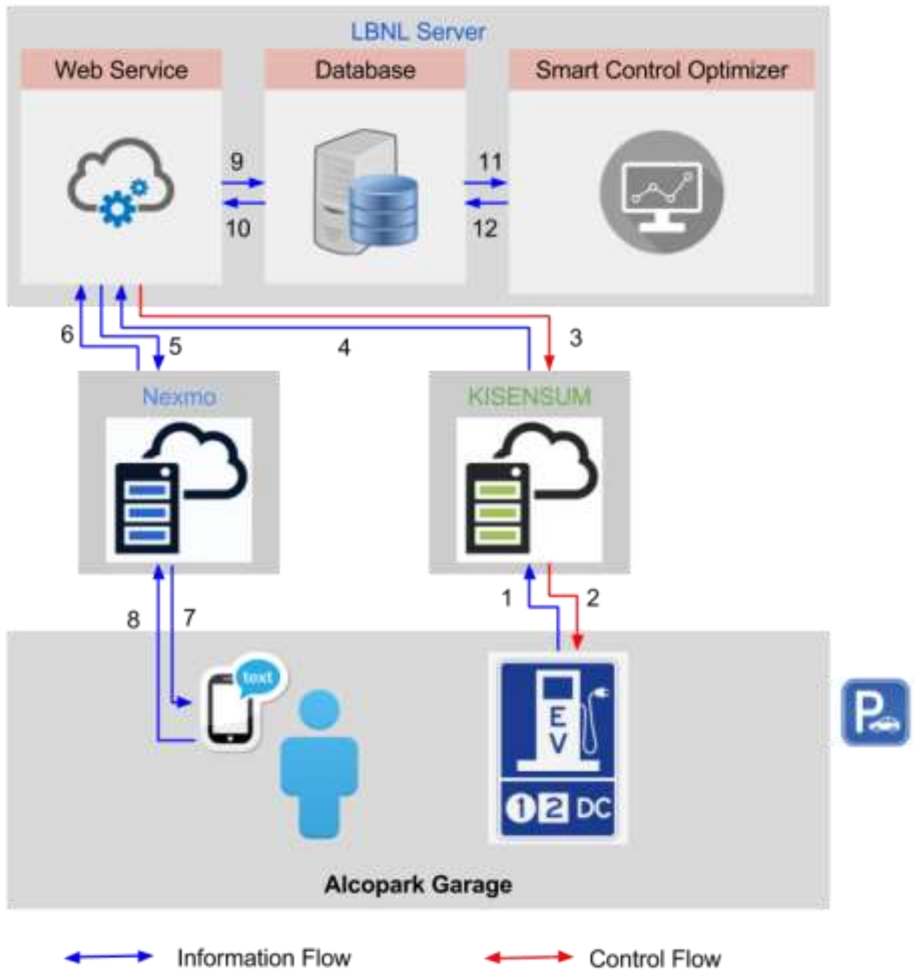
Source: Lawrence Berkeley National Laboratory

Public Smart Charging Strategy and Approach

For privately owned vehicles, the goal of the proposed smart charging framework was to reschedule the power time series measured in discrete time segments or any charging session on the same day. LBNL’s previous work describes the framework with the following key structures/assumptions: (1) The order of the measured power in time series is preserved (because the power that electric vehicle support equipment draws depends on the state of charge of the EV being charged); and (2) the charging is preemptive, which means the rescheduled charging load is equal to the original load and the charging tasks are interruptible without any decrease in the state of charge of the EV.

The public station charging control system required engagement of the EV drivers as shown in the system architecture schematic in Figure 12. The project team configured a physical server located at LBNL with several software programs written or applied in this project that included (1) interface with a web-based text messaging service, Nexmo, to communicate directly with public station users; (2) web-page forms for receiving anticipated session end times and charging energy needs from public station users; (3) a database to store anonymized charging station data; and (4) a smart charging optimization code for creating cost-minimizing charging schedules that met drivers’ needs. As with the fleet charging control, software created in this project that was located on the Kisensum server communicated to the public charging stations via the ChargePoint API, the charging station, the charging station vendor, and the charging power controller and optimizer.

Figure 12: System Architecture for Smart Charging Control of Public Charging Stations



Source: Lawrence Berkeley National Laboratory

The charging of privately owned EVs is different from that of fleet EVs. Most fleet vehicles can fully recharge overnight and be ready for use the next day. However, privately owned EVs usually park in the garage for a short period, and drivers need to charge their vehicles enough to avoid compromising their next trip. This can cause "range anxiety" for drivers of charging-controlled EVs due to unexpected less power. In this study, the participation in the pilot study for controlling the charging during public charging sessions was voluntary, while LBNL provided incentives to those who charged at the AlCoPark garage more than once a week.

Considering these factors, LBNL requested the drivers to provide (1) their estimated departure time; and (2) the estimated energy (kWh) or distance (miles) required. LBNL fed participants' charging request data into the charging control optimization algorithm and generated the optimal charging plan for each current active charging session. In general, the algorithm reduced the stacked charging power of concurrent charging sessions by staging the charging power sequence in different time slots. When the charging was finished or the charger was plugged out, the optimal charging plan was terminated immediately. At the current timestamp, the controlled charging station was reset back to normal.

The top priority of a smart charging control system is that the requested amount of charging power is guaranteed by the end of the charging session without any compromise of the charging request unless the vehicle gets fully charged or the driver unplugs the vehicle earlier than the submitted departure time.

As shown in Figure 12, the smart charging control system for public EVs includes the following main components: (1) an optimizer for computing the optimal charging power sequence; (2) a database for storing all the charging session data, the facility meter data and the charging request message; (3) a web-service for interacting with the pilot study participant to handle the charging request; (4) an API hosted by Kisensum for bridging the LBNL server end and the charging station; and (5) an API hosted by ChargePoint for managing the charging station's power settings. Among those components, the database, the web-service and the optimizer are hosted on the LBNL server. Kisensum developed a function to bridge the LBNL server and the ChargePoint API for the data exchange. Similarly, Kisensum developed an interface for smart charging control of the charging stations for the fleet vehicles only, as well as the DCFC charger. The main capabilities of the LBNL server and the Kisensum server are:

- LBNL Server:
    - Web-service to: 1) handle smart charging requests; 2) interact with users; 3) data collection; and 4) issue control commands.
    - Database: storage for all session data, meter data, smart charging requests.
    - Smart control optimizer: charging schedule optimization.
- Kisensum Server:
    - Communicates with each electric vehicle supply equipment (EVSE) via ChargePoint API.
    - Sends the charging session information (including user ID) from the EVSE to the LBNL server.
    - Sends and implements the optimal charging power settings from the LBNL server to the controlled EVSE.

The following sections describe the details of the communication and the charging control information exchange in the system.

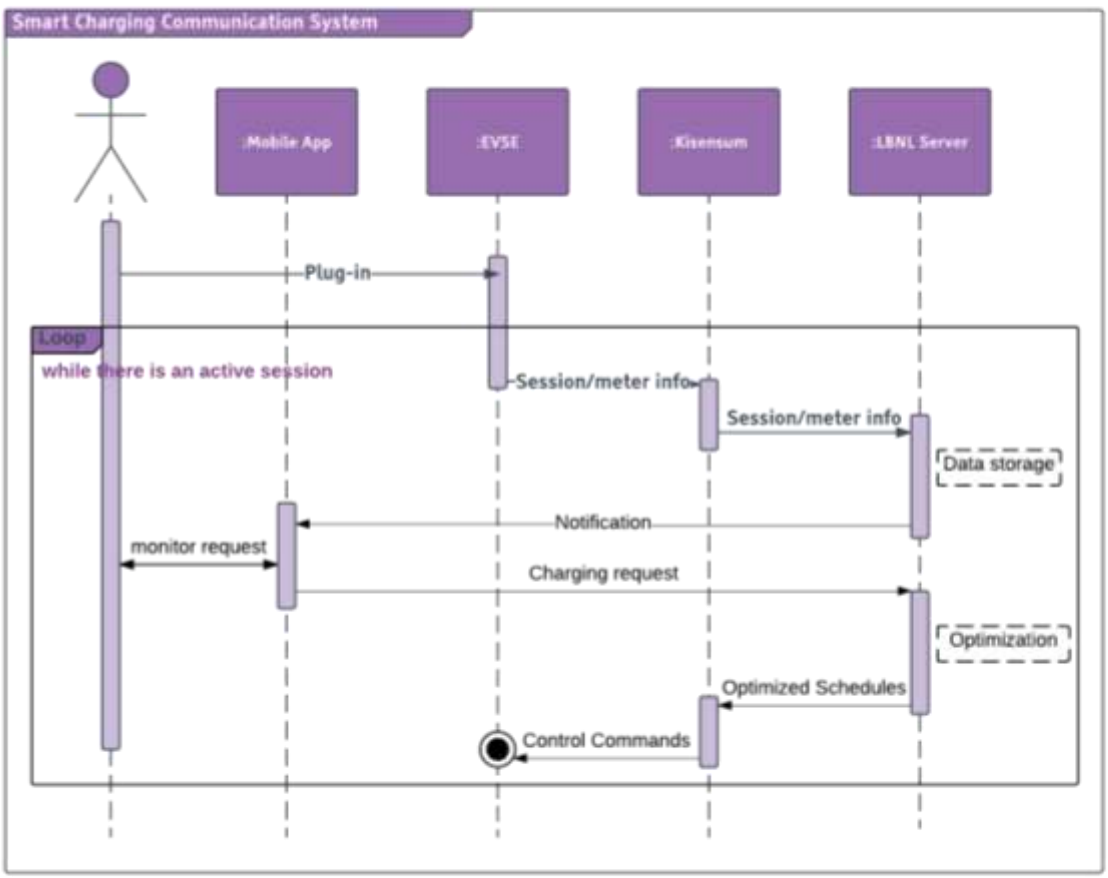
Communication Information Exchange

In the smart charging system for public EVs, as shown in Figure 13, LBNL developed a mobile application for interacting with the pilot study participant. When the driver plugs in the vehicle and activates the charging session, the Kisensum server captures the active charging session and passes the session data to the LBNL server. After checking whether the active charging session belonged to one of the pilot study participants in the database, the server sends a "Welcome" text message to the driver through the web-service. The text message provides a link to a webpage for submitting/modifying the charging request. The driver provides the estimated departure time and the estimated travel distance in miles or energy in kWh for the next trip. Drivers who agree to participate in the smart charging control can go to the webpage using the same link and check on the charging status at any time during the active session period.

The Kisensum server communicates with the charging station (EVSE) through the ChargePoint Web Services API (ChargePoint, 2014) to administer charging stations connected to the ChargePoint network. When exchanging data between a browser and a server, the data can only be text. The data exchanged between the LBNL server and the Kisensum is the charging session and meter data, which is in JSON format.

In the communication system for public EVs, LBNL uses a Short Message Service (SMS) provider to send/receive notifications and charging requests to/from drivers, as illustrated in Figure 13.

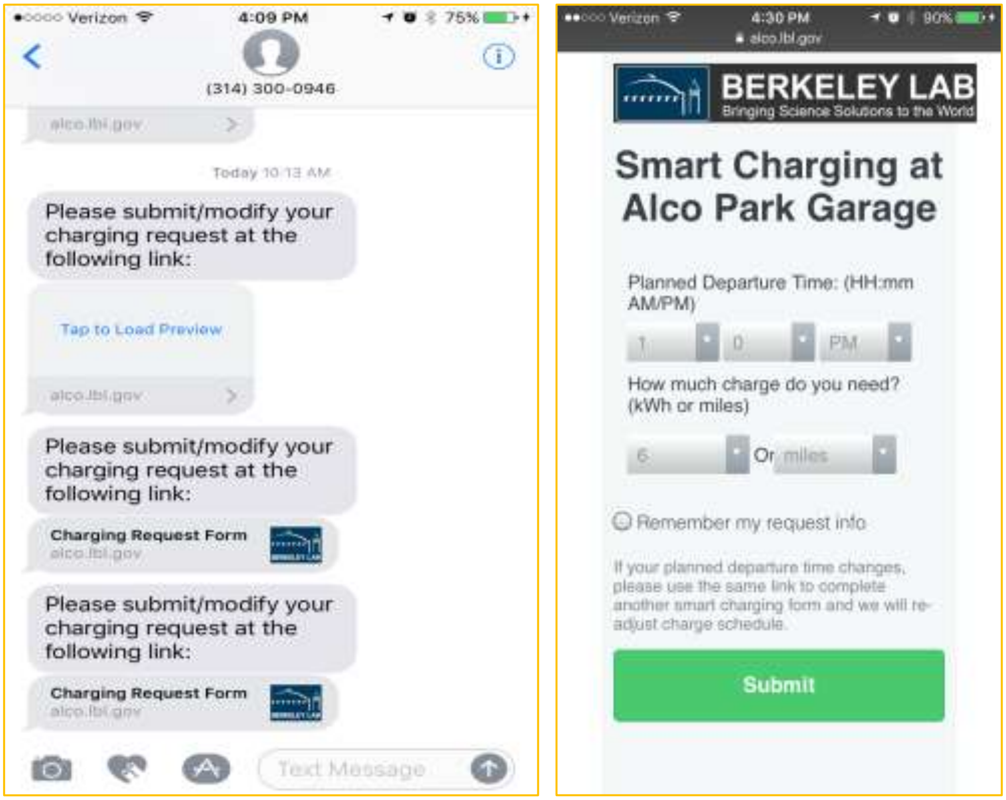
Figure 13: Smart Charging Communication System for Public Electric Vehicles



Source: Lawrence Berkeley National Laboratory

Figure 14 shows the SMS interactive system between the LBNL server and the study participant. In this study, the participant only received the text message from the LBNL server when plugging the vehicle into the controlled charging stations at the AlCoPark garage. The charging started as usual until the participant submitted the charging request, as shown in Figure 14 (right). On the same webpage, the participant could change the departure time and/or the energy charge needed at any time during the charging session.

Figure 14: Communication Interactions between the Lawrence Berkeley National Laboratory Server and the Participant



Source: Lawrence Berkeley National Laboratory

Charging Control Information Exchange

When participants submit their charging requests to the LBNL server through the web-service, the optimizer in the server first detects whether the message is new. If so, the optimizer initiates the optimization immediately and updates the optimized charging power sequence for all the controlled charging sessions in the database. Meanwhile, the LBNL web-service sends all the optimized charging power sequences to the Kisensum server in the JavaScript Object Notation (JSON) format. Last, the Kisensum server implements the optimized charging power sequences in the charging stations into which the participants' vehicles plug.

Public Smart Charging Optimization Algorithm Formulation

As in previous work (Kara et al., 2015), the EV charging session start and end times are assumed to be available to the controller. In addition, it was assumed that there was no modulation of charging power through the optimization. In this study, in addition to the scheduling algorithm in (Kara et al., 2015), the control algorithms with different approaches to re-optimization as EVs initiate and end charging sessions were tested. The scheduling algorithm by the order of the variables, the constraints, and the problem formulation is described below. For each day's charging scheduling, a day was divided into 15-minute demand intervals. Each smart charging optimization period was defined as having a start time, t_{start}, and an end time, t_{end}. Each individual EV charging session, *i*, had an arrival time t_a^i, and a departure time, t_d^i. For each charging session, a column vector was created using the power measurement for every time slot in $[t_a^i, t_d^i]$. If the charging duration was less than the session duration, the time series was zero-padded to fill the size of the optimization time period $[t_{start}, t_{end}]$. The power time series for each EV charging session i was given as follows:

$$P^{(i)} = [P_1^{(i)}, P_2^{(i)}, , P_k^{(i)}]^T \quad (3)$$

Where k was the total number of 15-min time slots in $[t_{start}, t_{end}]$. Q^i elements Q_j^i correspond to the j non-zero element of P^i. M^i was defined as the total number of non-zero power measurements in charging session i. The goal was to reschedule the time slots t_j^i in $[t_a^i, t_j^i]$, t_j^i corresponding to Q_j^i without changing their order.

The following formal constraints were introduced in (Kara et al., 2015) to capture the precedence and the session duration constraints. Additionally, a constraint to t_j^i to keep the continuous charging order the same as the original charging session was included. Charging control option (A) controlled the charging session start time while maintaining the same power time series $P^{(i)}$ as the original. Charging control option (B) discretized the original charging session into 15-minute charging blocks without changing the order of the power time series $P^{(i)}$.

(1) Option A:

$$\left.\begin{array}{r} \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \geq \mathrm{t}_\mathrm{start} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \leq \mathrm{t}_\mathrm{end} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \geq \mathrm{t}_\mathrm{a}^{(\mathrm{i})} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \leq \mathrm{t}_\mathrm{d}^{(\mathrm{i})} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} + 1 = \mathrm{t}_\mathrm{j+1}^{(\mathrm{i})} \end{array}\right\} \quad \begin{array}{c} \forall \mathrm{i} \in [1, \mathrm{N}], \\ \forall \mathrm{j} \in [1, \mathrm{M}^{(\mathrm{i})}] \end{array} \quad (4)$$

(2) Option B:

$$\left.\begin{array}{r} \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \geq \mathrm{t}_\mathrm{start} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \leq \mathrm{t}_\mathrm{end} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \geq \mathrm{t}_\mathrm{a}^{(\mathrm{i})} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \leq \mathrm{t}_\mathrm{d}^{(\mathrm{i})} \\ \mathrm{t}_\mathrm{j}^{(\mathrm{i})} \leq \mathrm{t}_\mathrm{j+1}^{(\mathrm{i})} \end{array}\right\} \quad \begin{array}{c} \forall \mathrm{i} \in [1, \mathrm{N}], \\ \forall \mathrm{j} \in [1, \mathrm{M}^{(\mathrm{i})}] \end{array} \quad (5)$$

Constraints using a binary decision matrix to represent charging or non-charging time slots within the optimization duration were included. A binary vector x_j^i was created to include k binary decision variables. Each element in this vector represents a candidate time slot at which Q_j^i could be positioned. Row vectors $x^{(i,j)}$ $\forall i \in [1, M^i]$ and $x_k^{(i,j)} \in \{0, 1\}$ were defined as well $\forall k \in [1, K]$.

A binary decision matrix X^i was formed for these binary vectors x_j^i in each charging session $\forall i \in [1, N]$. As shown below, the individual decision variables $x_k^{(i,j)}$ form the elements of the binary decision matrix X^i.

$$\mathrm{X}^i = \begin{bmatrix} x_1^{(i,1)} & \cdots & x_K^{(i,1)} \\ \vdots & \ddots & \vdots \\ x_1^{(i,M^i)} & \cdots & x_K^{(i,M^i)} \end{bmatrix} \tag{6}$$

As proposed in (Kara et al., 2015), the variables in the constraints given in the constraints Option A and constraint Option B were defined as follows:

$$t^i = \mathrm{X}^i O,\ where\ O = \begin{bmatrix} 1 \\ \vdots \\ K \end{bmatrix} \tag{7}$$

The aggregate power vector for the charging station $AP^d = \sum_{i=0}^{N}(\boldsymbol{P}^{(i)})$ for the day d was given as follows:

$$AP^{(d)} = \begin{bmatrix} Q^{(1)} \\ \vdots \\ Q^{(N)} \end{bmatrix}^T \begin{bmatrix} \mathrm{X}^{(1)} \\ \vdots \\ \mathrm{X}^{(N)} \end{bmatrix} \tag{8}$$

This study builds on the general optimization framework as proposed in (Kara et al., 2015). The optimization goal was to maximize the benefits of the smart charging control algorithm from a EV charging service provider's perspective. As in a typical TOU rate structure, the energy charges were calculated based on the amount of energy consumed over the period using the corresponding hour's TOU energy rate. The demand charges were calculated based on the maximum power demand for specific time periods of the day during the billing period. In the summer season, there were separate demand charge rates for different periods – on-peak, mid-peak and any time peak demand multiplied by the demand charge rates (see Table 2).

In the proposed smart charging framework, EC^d was defined as the energy charge for day d in a month with D Days (i.e. $\forall d \in [1, \ldots, D]$). Then, DC_h was defined as the demand charge for each time period h of the day h of any month. In the PG&E E-19 TOU rate structure, the monthly demand charges in winter season were calculated based on the maximum demand in two time periods anytime and part-peak (i.e. 8:30 a.m.-12:00 p.m. and 6:00 p.m.-9:30 p.m.). In the summer months, the demand charges included three components: (1) maximum demand in anytime of the billing month; (2) maximum demand in on-peak time period; and (3) maximum demand in part-peak time period. Formally, the monthly bill was calculated as follows:

$$f(DC_d, EC^d) = \sum_{\forall d} DC_h + \sum_{\forall d} EC^d \tag{9}$$

In the optimization problem, the energy charge EC^d for any day d in a billing period was calculated as shown in Equation 10. The energy price for each time slot j was defined as a column vector ER. For time period h within day d, a subset of the entire daily aggregate power vector AP^d is defined as AP_h^d.

$$EC^d = AP^d \times ER \tag{10}$$

The maximum demand for the daily time period h must be accurately known beforehand for the entire month. However, it is not a valid assumption when predicting the maximum demand for the forthcoming month due to the variations from the base load and the charging sessions. In the proposed smart charging framework, the peak aggregate power values were defined for each period h as $AP^{d}_{peak,h}$. In the daily optimization, $AP_{peak,h}$ represent the historic values for each day in $[1, \dots, d-1]$. Hence, the maximum of the historic $AP_{peak,h}$ values until $d-1$ was as follows:

$$AP^{d-1}_{max,h} = \max(AP^{1}_{max,h}, \dots, AP^{d-1}_{max,h}) \tag{11}$$

Therefore, the monthly demand charges were calculated based on $AP^{d}_{max,h}$ and the demand rates DR_h for each period:

$$DC_h = AP^{D}_{max,h}\, DR_h \tag{12}$$

By using Equation 13, the demand charges were limited based on the maximum daily demands until the current day. The following optimization problem was formed to minimize the daily energy cost and the demand charges with time period h and day d as decision variables.

$$\min_{\mathbf{x}^{(i)}, AP^{(d)}_{max,h}} (AP^{(d)}_{max,h} DR_h + EC^{(d)}) \tag{13}$$

Subject to the constraints Option A or Option B and the following additional constraints:

$$\forall h \in [1, TP] \begin{cases} AP^{(d-1)}_{max,h} \leq AP^{(d)}_{max,h} \\ AP^{(d)}_{h} \leq AP^{(d)}_{max,d} \end{cases} \tag{14}$$

As seen in Equation 14, the current maximum demand $AP^{(d)}_{max,h}$ was insured to be greater than or equal to the maximum historical value $AP^{(d-1)}_{max,h}$ for period h. Note that the demand charges for each period h were not set by the current day d if none of the current peak values $AP^{(d)}_{max,h}$ exceeded the historical maximum values $AP^{(d-1)}_{max,h}$.

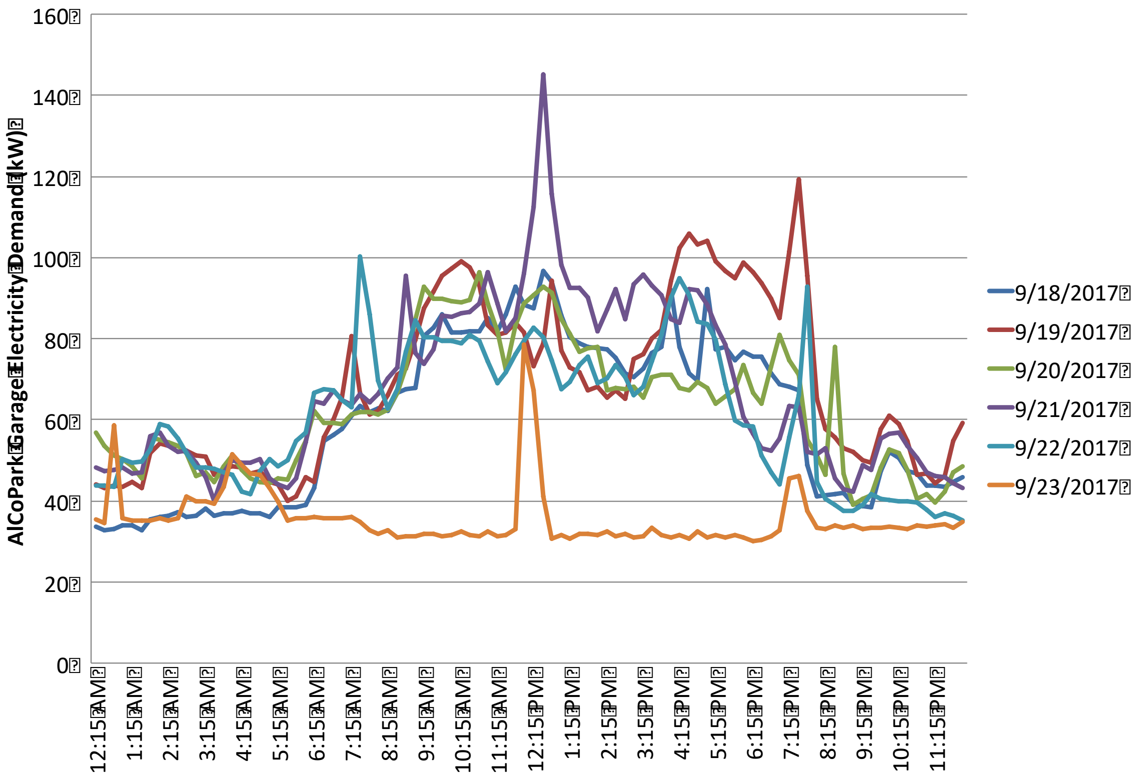
The following section presents the general smart charging framework for the public EVs, which includes the pilot study participants' outreach and recruitment, the field test of the proposed control algorithm and the implementation of the entire smart charging control system. The effect of the smart charging control algorithm in terms of reducing the monthly energy and demand costs of EV charging are presented.

Direct Current Fast Charging Smart Charging Strategy and Approach

The installed DCFC charging station supported both CHAdeMO and SAE Combo Charging System with a 50 kW maximum output. To reduce the power spike from a DCFC charging session on the total demand, a control strategy was developed that reduced the charging power of concurrent fleet Level 2 charging sessions to Level 1 charging power level.

In August 2017, AlCoPark garage installed a Level 3 DCFC charging station (ChargePoint model CPE 200) with 1 SAE Combo and 1 CHAdeMO connectors for use by both public and fleet EVs, in particular for the quick turnaround of fleet vehicles. The first charging session on this DCFC charging station was observed on September 1, 2017. Figure 15 shows a clear spike of 30-50 kW for about 30 minutes during the DCFC charging session.

Figure 15: AlCoPark Garage Electricity Demand in a week of September 2017

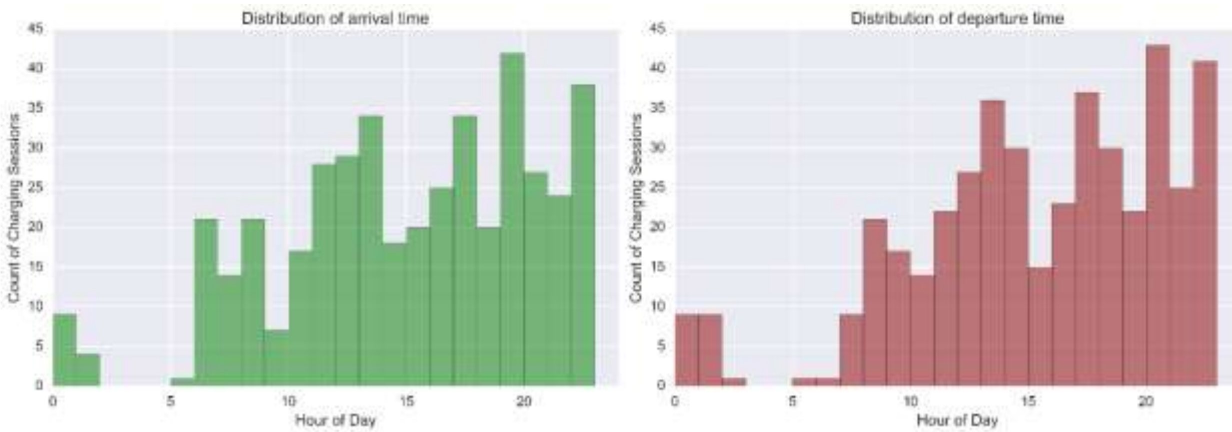


Source: Lawrence Berkeley National Laboratory

To better understand the charging behavior of DCFC charging sessions, the researchers analyzed the arrival/departure times and the monthly number of DCFC charging sessions. Figure 16 shows that the majority of charging sessions were in the afternoon hours. When the spike of DCFC charging power was observed during the day, especially during on-peak hours, the facility manager started "Happy Hours" that provided lower costs for public DCFC charging after 7 p.m. to encourage a shift to off-peak hours.

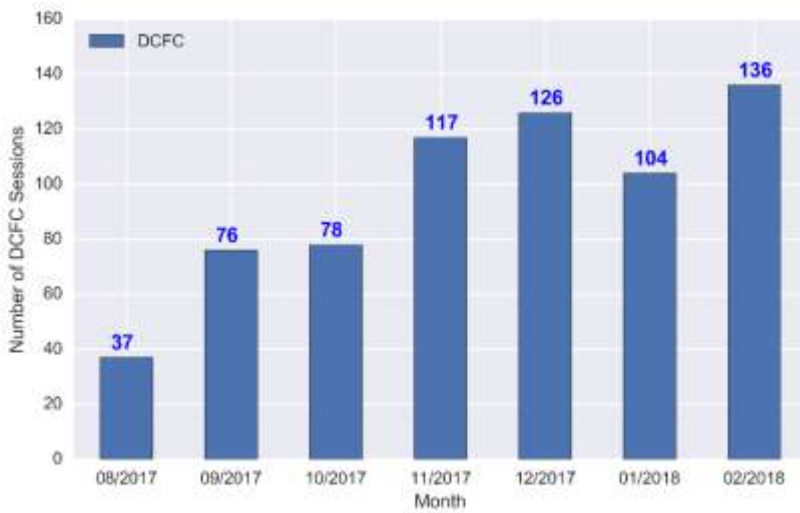
While the monthly facility peak demand increased along with the number of charging sessions, it increased even further with the use of the DCFC charging station. Figure 17 presents the monthly DCFC charging sessions since the first use of the DCFC charging station. There were 136 monthly DCFC charging sessions by February 2018. There were about 3.5 DCFC sessions per day, on average, with more sessions on weekdays compared to weekend days. Therefore, there was a good chance that the monthly peak demand and/or on-peak demand in summer period would be set by DCFC charging sessions.

Figure 16: Arrival/Departure Time of Direct Current Fast Charging Sessions



Source: Lawrence Berkeley National Laboratory

Figure 17: Monthly Direct Current Fast Charging Sessions in 2017



Source: Lawrence Berkeley National Laboratory

To reduce the power spike from a DCFC charging session on the total demand, a control strategy limiting the charging power of concurrent fleet Level 2 charging sessions to Level 1 charging power level was implemented. The specific control logic for reducing the demand of fleet sessions during DCFC charging sessions was as follows: For every minute, whenever the smart charging control system received a "DCFC session start" notification, the system took a reading of the DCFC demand, and:

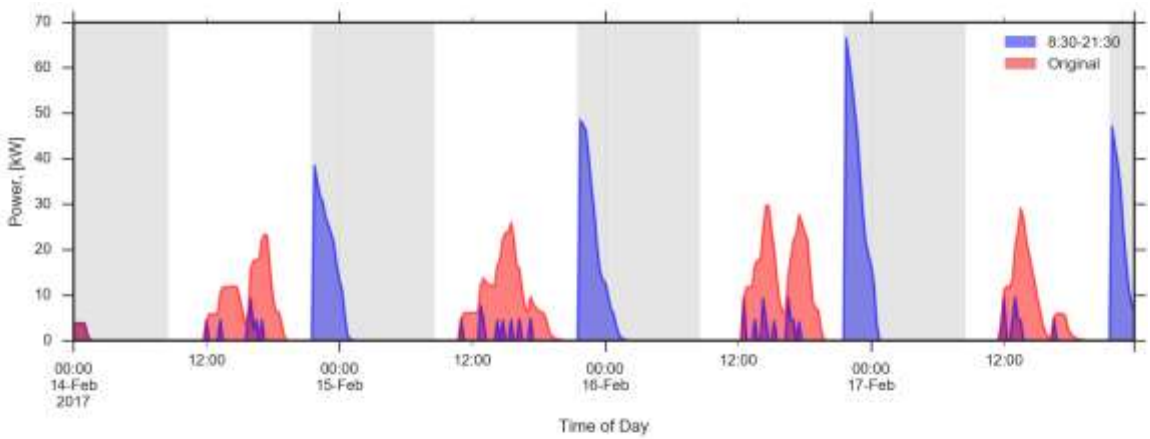
- If the load was more than 10 kW, fleet stations 002, 003 and 004 were set to charge at 1.65 kW (station 001 was not controlled).
- If the load was less than 10 kW, any fleet station (002, 003, and 004) that had been set to 1.65 kW due to a DCFC override was returned to its default state.

CHAPTER 4: Smart Charging Results

Fleet Smart Charging Results

On February 9, 2017, the first control strategy was implemented: no charging for fleet stations between 8:30 a.m. and 9:30 p.m., except ALCOBASE4000-002, 003 and 004. Figure 18 shows the comparison of the charging power before and after the implementation of charging control between February 14, 2017 and February 17, 2017. The red areas in the graph represent the original charging power without any restriction on charging sessions, and the blue areas represent the actual charging power from the controlled charging stations. All the charging sessions on the controlled stations were postponed successfully from high cost periods (between 8:30 a.m. and 9:30 p.m.) to lower cost periods (after 9:30 p.m.).

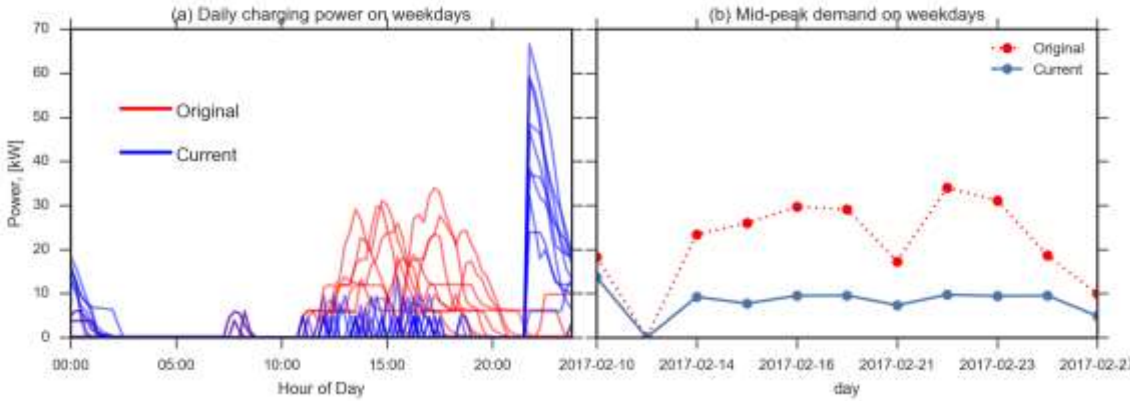
Figure 18: Comparison of Charging Power before and after Implementation on February 9, 2017



Source: Lawrence Berkeley National Laboratory

The mid-peak demand was reduced by 20kW between February 9, 2017 and February 27, 2017, as shown in Figure 19. However, a new higher peak demand of 68 kW was observed when all the controlled stations started to provide charging power at 9:30 p.m. This peak did not create a new monthly peak, however, due to the base load “valley” at that time, but there was a risk of setting a new peak with this course control scheme. After about two weeks of implementing this charging control, a staged scheduling approach was implemented.

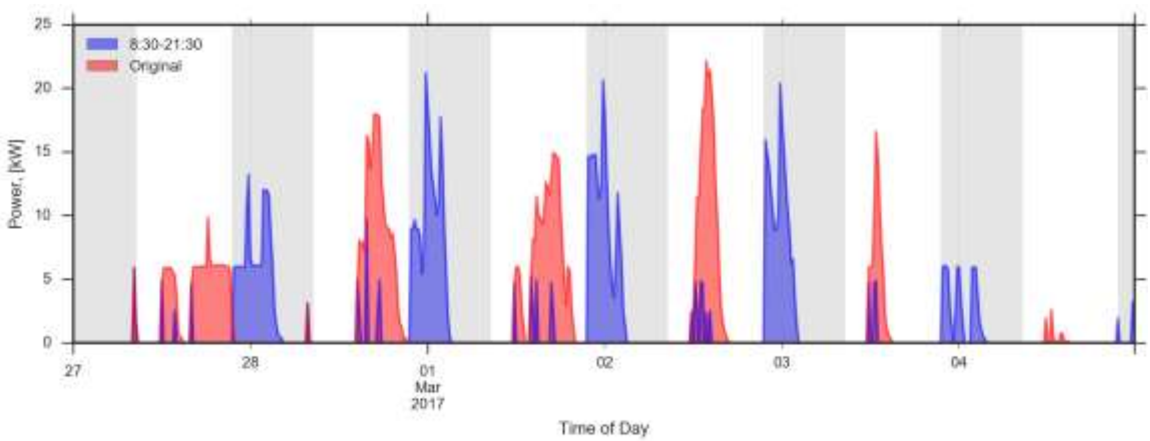
Figure 19: Effects of Charging Control of Fleet Electric Vehicles between February 9-27, 2017



Source: Lawrence Berkeley National Laboratory

On February 27, 2017, the staged approach was implemented with the following charging schedules: 4 ports starting at 9:30 p.m., 5 ports starting at 11:30 p.m., and 5 ports starting at 1:30 a.m. This fixed the issue of the new higher peak demand with the first control strategy, as shown in Figure 20. The new peak demand was very close to the original charging power and reduced energy charges by nearly half since most of the original charging sessions started during the on-peak period.

Figure 20: Comparison of Charging Power before and after Implementation on February 27, 2017

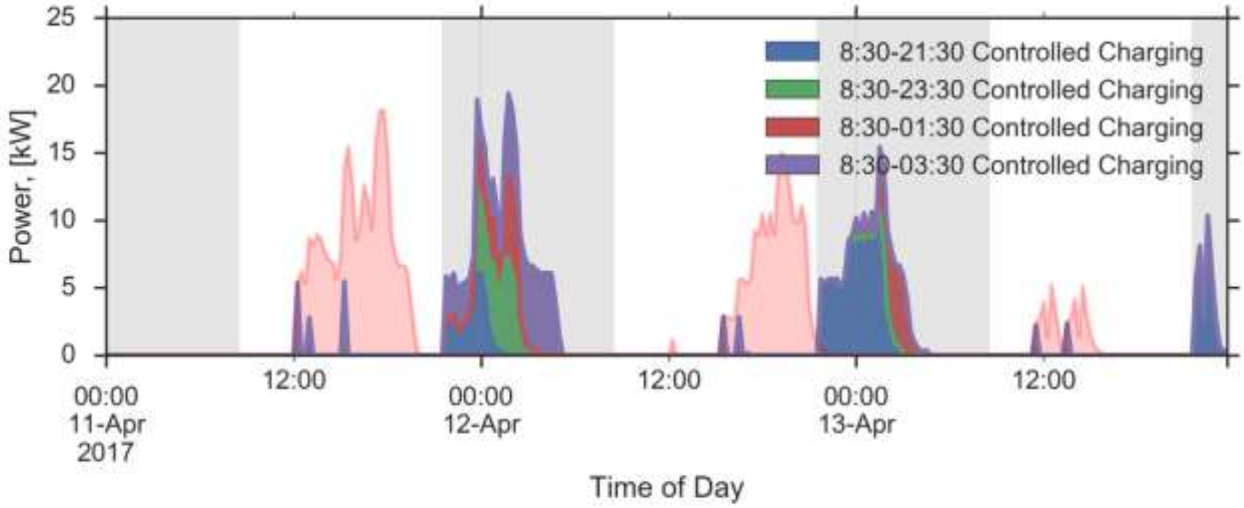


Source: Lawrence Berkeley National Laboratory

The promising results of the staged control strategy led to a further modification of the charging schedules on March 6, 2017: 4 groups of the delayed charging control stations (9:30 p.m., 11:30 p.m., 1:30 a.m., and 3:30 a.m.). The fleet management staff asked that fewer charging stations be subject to the restricted charging schedule so that they could do more on-demand charging. This reduced the savings potential of the smart charging strategy.

As shown in Figure 21, there were multiple charging power spikes at the start time of each scheduling period. Through this control strategy, the new peak demand did not exceed the original peak demand while shifting the charging power from the high electricity cost periods to the lowest period.

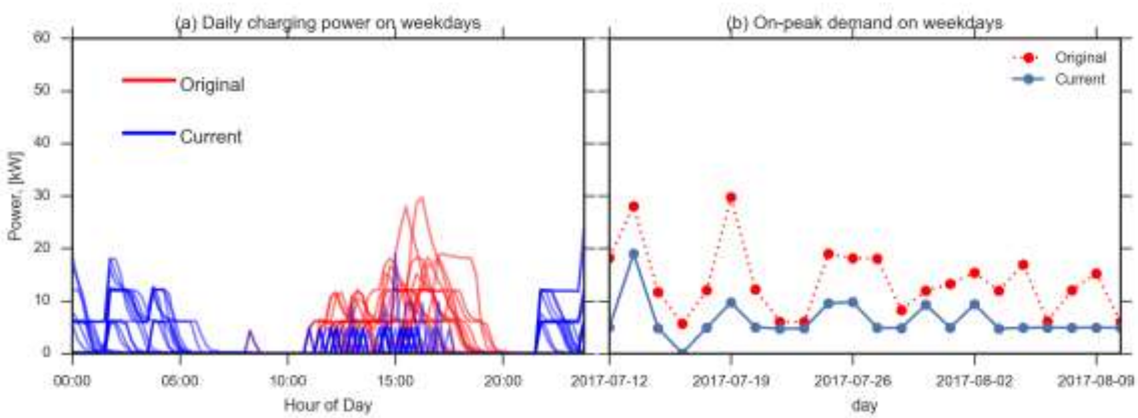
Figure 21: Comparison of Charging Power before and after Implementation on March 6, 2017



Source: Lawrence Berkeley National Laboratory

The scheduled smart charging has been continuously operating since its implementation in March 2017. As shown in Figure 22, the peak demand during the on- and mid-peak periods was reduced by 10.7 kW and 13.3 kW respectively during a week in the summer period.

Figure 22: (a) Daily Charging Power Profiles and (b) On-Peak Demand on Weekdays with the Control of Charging Stations for Fleet Electric Vehicles

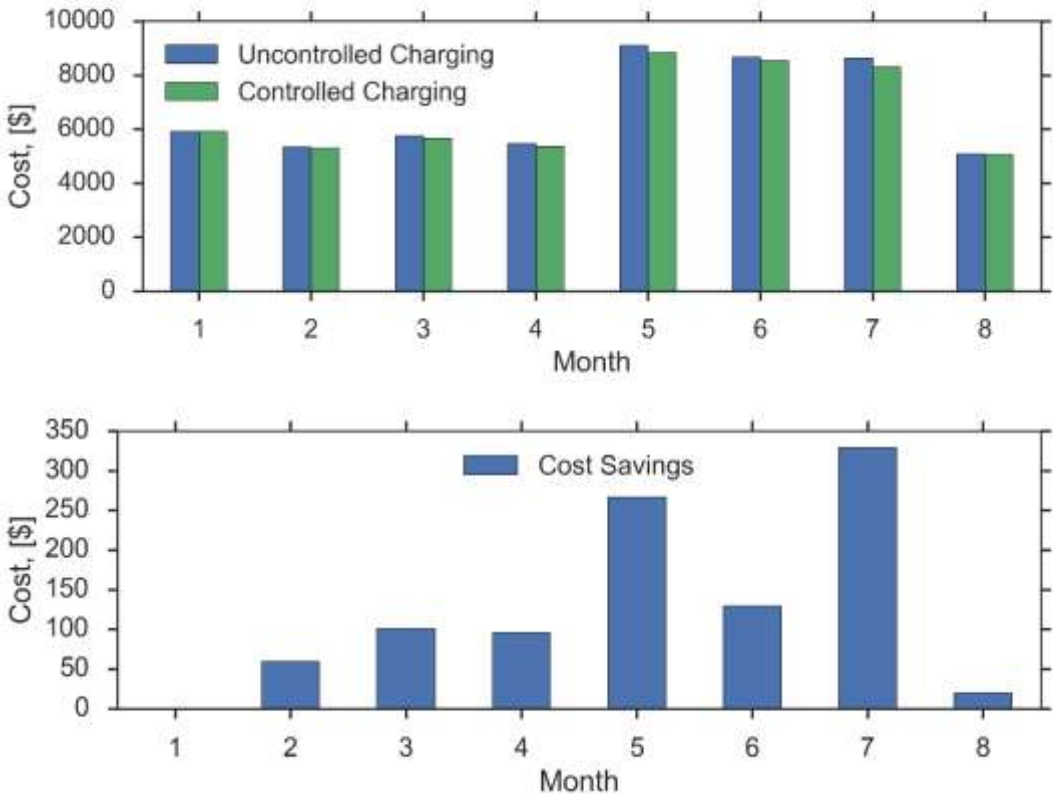


Source: Lawrence Berkeley National Laboratory

To calculate the demand and cost savings from the smart charging controls, the controlled charging session demand profiles were re-created as if they had not been controlled.
The data collected for each charging session included the connect and disconnect time. The demand profile of each controlled session was converted to the demand profile that would have existed had it not been controlled by assuming that session would have charged at its maximum rate, for example 6 kW for the Level 2 fleet and public stations, starting at the session connect time rather than the smart charging scheduled start time. The total energy delivered was the same for the re-created sessions as the actual controlled sessions. The E-19 tariff values were then applied to the aggregate re-created session profiles to calculate the costs

as if controls had not been implemented. These costs were compared to the actual costs to determine the demand and cost savings from the smart charging control approach. As presented in Figure 23, the implementation of the smart charging control of the fleet EVs achieved cost savings of $946 between February 2017 and early August 2017, representing 1.8 percent of the total utility bill in 2017. In the summer months (May-October), the total cost savings was $743 and the average savings was $241.

Figure 23: Comparison of Monthly Utility Costs from Uncontrolled and Controlled Charging of Fleet Electric Vehicles

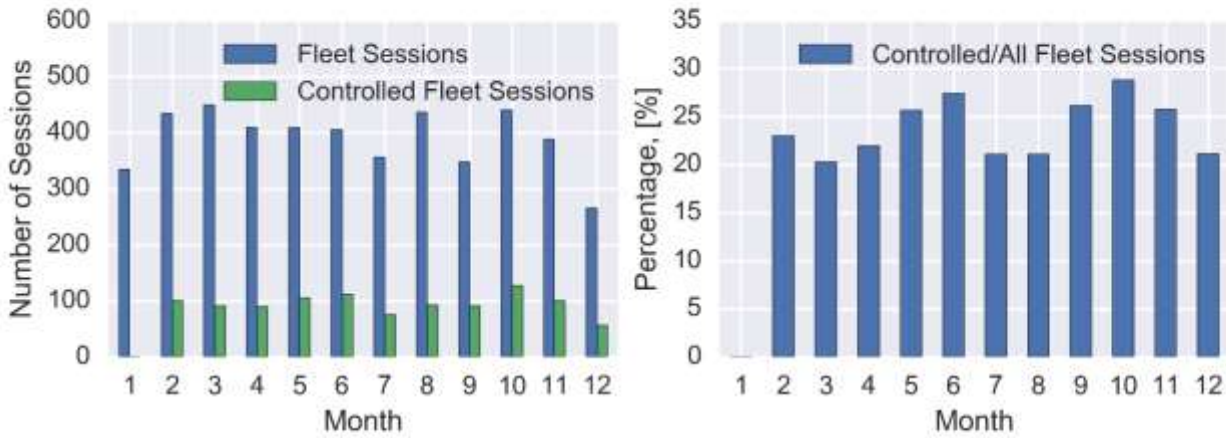


Source: Lawrence Berkeley National Laboratory

In 2017, nearly 1,000 charging sessions were controlled for minimizing the peak demand of fleet EVs, which was about 25 percent of the total fleet charging sessions. The number of controlled fleet charging sessions was around 100 sessions per month, as shown in Figure 24. In addition, the average cost savings per session was about $1.80 per session.

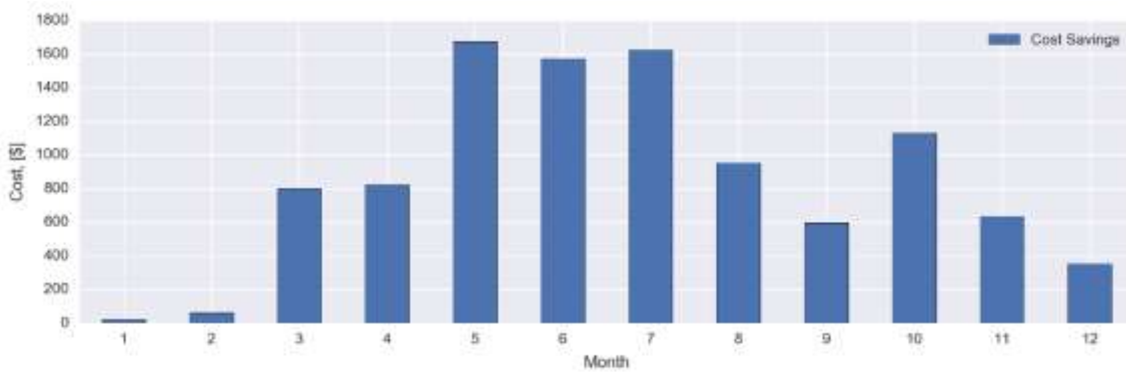
To date, 10 of 24 dedicated fleet charging ports have implemented the smart charging control. Hypothetically, if this smart charging control strategy were deployed for all fleet charging ports with all fleet charging sessions controlled, the annual cost savings was estimated to be $10,244 and the cost saving per session would be $2.40 ($3.20 in summer and $1.40 in winter).

Figure 24: Monthly Controlled/All Fleet Charging Sessions in 2017



Source: Lawrence Berkeley National Laboratory

Figure 25: Cost Savings from All Fleet Sessions being Controlled



Source: Lawrence Berkeley National Laboratory

Fleet Electric Vehicle Smart Charging Lessons Learned

The charging behavior indicated from the charging session dataset shows that most fleet EVs return to be charged during on-peak hours. This leads to very high demand charges from all the fleet EVs being charged simultaneously. Implementing smart charging control on only 25 percent of the fleet charging sessions reduced 44.3 percent of the original on-peak demand without any impact on the use of fleet EVs the next day. The larger number of fleet EVs compared to the number of chargers limits the cost savings potential from the smart charging control. In addition, fleet staff could not rotate vehicles to available chargers outside of garage operating hours (7 a.m.-7 p.m.).

Given the current limitations, a better coordinated fleet charging system would improve the performance and reduce utility costs by linking fleet vehicle trip management with the smart charging control.

Public Smart Charging Results

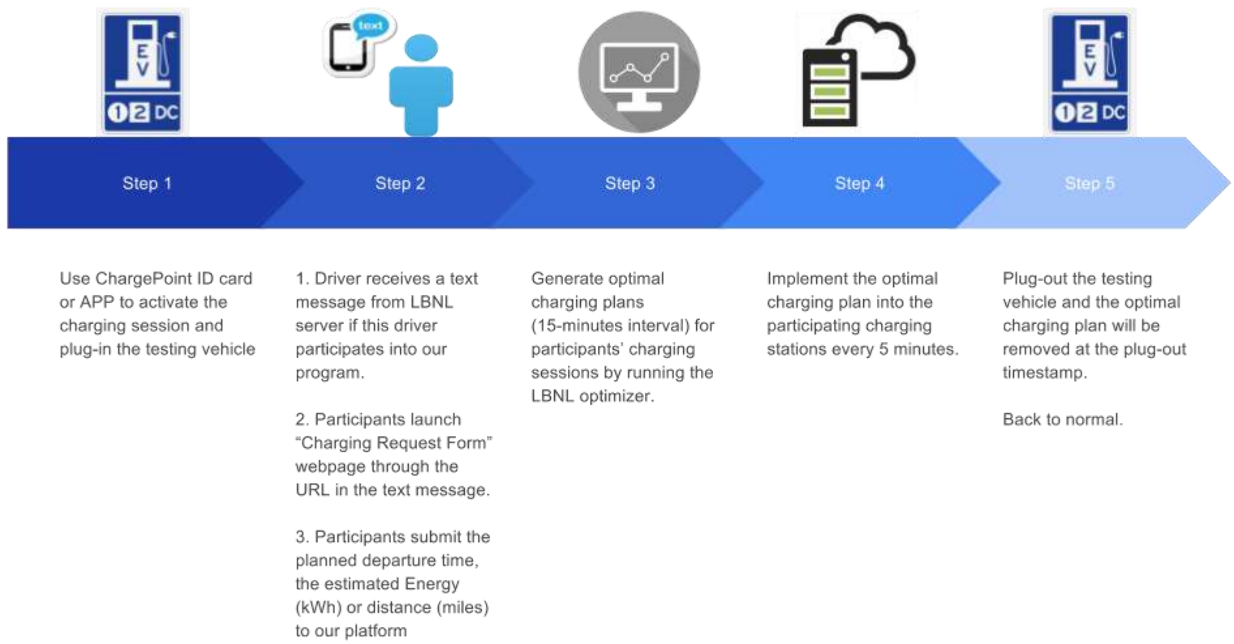
Pre-Pilot Field Testing

The researchers conducted field tests using the project team members' vehicles to validate the performance of the smart control algorithm for the public charging stations and the entire communication and control architecture. Main tasks included:

- Testing the control and communication flow of the platform end-to-end.
- Validating the capabilities and functions of each system component.
- Validating the optimal charging control algorithm for demand management.

Figure 26 depicts the end-to-end testing of the smart charging control system for public EVs at the AlCoPark garage.

Figure 26: End-to-End Testing of Smart Charging Control System for Public Electric Vehicles



Source: Lawrence Berkeley National Laboratory

The participants' ChargePoint user IDs were stored in the LBNL database. Participants received a text message within one minute after they connected their EV and activated a charging session. A webpage link, "Charging Request Form," was sent in the text message as shown in Figure 14. Participants entered their planned departure time and estimated needed energy (kWh) or distance (miles) for their trips following charging at the AlCoPark Garage. After participants submitted their requested information to the LBNL server through the web service, the charging control optimizer used the participants' charging request data to generate the optimal charging plan for each current active participating charging session. The optimal charging plan was sent to the participating charging stations through the Kisensum server and

ChargePoint API. When charging was completed or the charging session was ended by the participant disconnecting from the station, the optimal charging plan was terminated immediately and the controlled charging station was reset back to normal operation. During the charging process, drivers could check the status of their charging sessions at the "Charging Request Form" webpage at any time to see how much energy had been delivered and what time the charging request would be completed.

On May 4, 2017, two Nissan Leaf electric vehicles owned by study researchers were used to conduct an end-to-end testing of the smart charging control for public EVs. Table 3 presents the testing vehicles for the control of public charging stations. For this test, the performance of the smart control algorithm was evaluated in terms of the following metrics:

- Optimized charging power sequence vs. actual charging power sequence.
- Requested charging power energy vs. actual charging power energy.

During the testing, the real charging power was automatically logged from the charging stations to the database to validate against the optimized charging power sequence. In addition, the actual charged energy kWh was compared with the requested energy kWh and/or travel distance in miles. Through the end-to-end communication and control testing, the capability of the smart charging control system for minimizing the contribution of public charging demand of multiple EVs to peak demand was demonstrated without negative impact on the drivers' charging needs.

Table 3: Testing Vehicles for Public Charging Stations

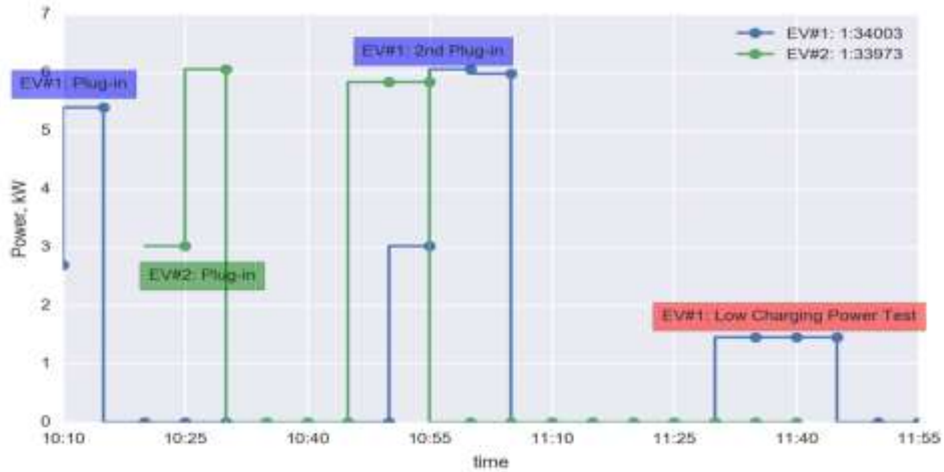
Participants	EV Model	Capacity (kWh)
# 1	2017 Nissan Leaf	30
# 2	2016 Nissan Leaf	24

Source: Lawrence Berkeley National Laboratory

During the testing period, testing for both EV #1 and EV #2 followed the optimal charging plan well except that the vehicles stopped being charged when the planned charging power was less than a certain level. To address this issue, the charging plan of EV #1 was interrupted and the approximate lower limit of the charging power was identified as 1.5 kW. This is a significant limit that was applied to all controlled charging sessions. Previous studies have assumed that 0 kW was the lower limit charging power constraint in simulating and analyzing optimal charging control scenarios. A comparison between the meter readings of 2.30 kWh and the reported 2.37 kWh from the ChargePoint application was observed to confirm that the scheduled charging power plans were implemented sufficiently accurately.

After the initial testing, the charging power lower limit was set to 1.5 kW to avoid having a charging vehicle's own battery protection override a charging request. On August 21, 2017, the team conducted another test of the charging control system to validate the charging power lower limit set point.

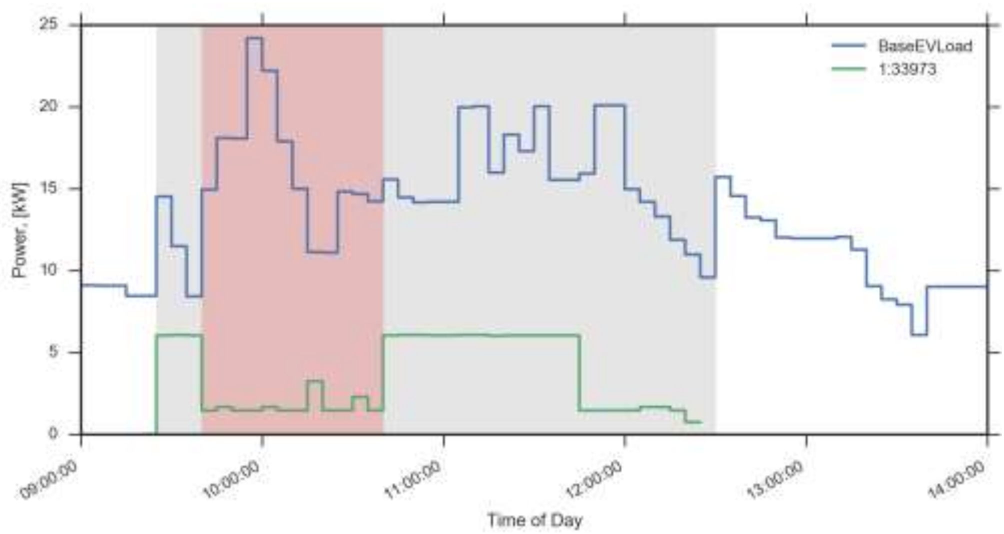
Figure 27: Testing Events on May 4, 2017



Source: Lawrence Berkeley National Laboratory

As shown in Figure 28, there was no power interruption during the testing period (red area). After this, the option of "opt-out" charging control during the charging session was tested. It was observed that the charging power was reset back to the normal level of around 6 kW within 5 minutes. A driver could come back to participate into the program again by submitting a new charging control request on the same webpage.

Figure 28: Testing of the Charging Power Lower Limit for Public Electric Vehicles



Source: Lawrence Berkeley National Laboratory

As described in Table 4, at 11:43 a.m., a driver sent a new message to the server and requested a revised departure time of 12:30 p.m.. By the end of the charging session, the vehicle received nearly 10.5 kWh in comparison to the requested energy of 10 kWh.

In July 2017, a recruitment letter was sent to potential drivers who were charging at least twice per week at the public charging stations. By October 2017, LBNL had recruited 7 active participants (and 3 that agreed to participate but did not) into the pilot study. During this period, there were 33 participating charging sessions.

Table 4: Smart Charging Control Logs on the Testing Event

Timestamps	Actions in the Charging Control
09:36:55	Driver received a text message and requested 10kWh charging energy.
09:40:00	Optimal charging started and it was observed that the charging power was low when the total charging power of all public stations was high.
10:36:32	Driver sent the "max-out"/"opt-out" message to opt-out the program.
10:40:00	Optimal charging control was interrupted and the charging power was reset back to normal.
11:43:44	Driver sent another message to the server and requested the leaving time at 12:30 p.m..

Source: Lawrence Berkeley National Laboratory

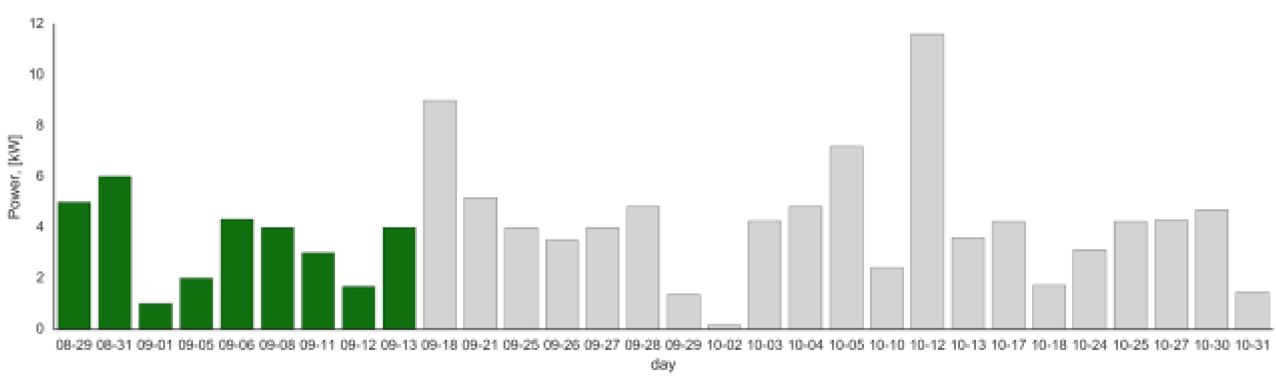
The researchers calculated the following metrics for each participant: participating sessions, contribution to the daily peak electricity demand reduction, and charged energy kWh against requested kWh. An example of a participant performance report is shown in Table 5, Table 6, and Figure 29.

Table 5: Example Study Participant Report in Summer 2017

Month	August	September	October	Total
Charging Sessions	2	12	9	23
Participating Sessions	2	9	0	11
Participation Rate	100%	75%	0%	48%

Source: Lawrence Berkeley National Laboratory

Figure 29: Contribution to Daily Peak Electricity Demand Reduction in Summer 2017



Note: Daily peak demand savings shown in green are the amount of kW shed from this or/with other participants.

Source: Lawrence Berkeley National Laboratory

Table 6: Smart Charging Program Participation History

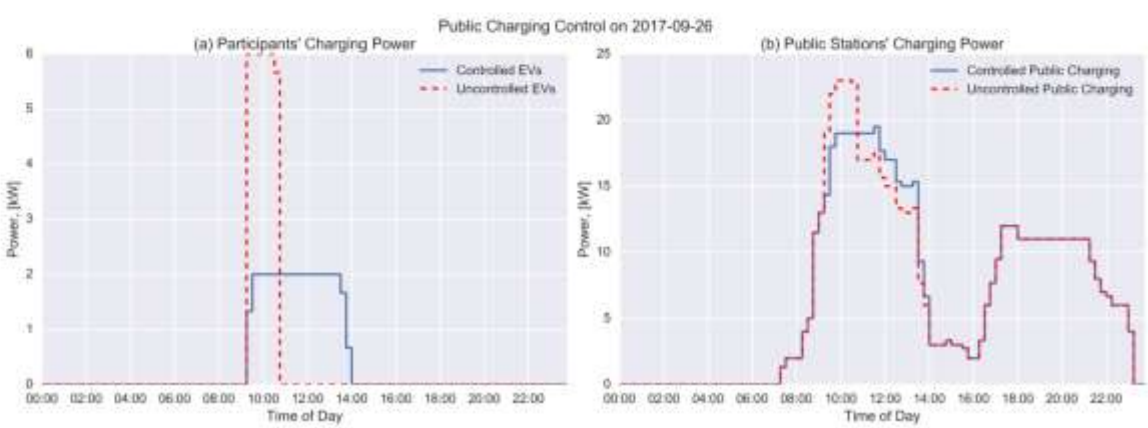
Date	Estimated kWh	Charged kWh	Meet Requested kWh/Miles	Charge To Full
8/29/2017	14.3	14.8	Y	n/a
8/30/2017	24.0	14.4	n/a	n/a
8/31/2017	24.0	15.4	n/a	n/a
9/1/2017	24.0	15.8	n/a	Yes
9/5/2017	24.0	14.9	n/a	Yes
9/6/2017	24.0	13.8	n/a	Yes
9/8/2017	24.0	16.5	n/a	Yes
9/11/2017	24.0	15.4	n/a	Yes
9/12/2017	24.0	14.2	n/a	Yes
9/13/2017	24.0	14.0	n/a	Yes
9/15/2017	24.0	9.5	n/a	Yes

Source: Lawrence Berkeley National Laboratory

Overall Performance of Public Smart Charging

The smart charging control system for public charging was launched on August 29, 2017. Pilot study participants contributed to reducing the daily peak demand and the on-peak demand in particular. Figure 30 presents an example of the charging control of one participant's EV charging on September 26, 2017. The dotted red line and solid blue line represent the power demand of the uncontrolled and controlled public EVs, respectively. The peak demand of the uncontrolled EV was reduced from 6 kW to 2 kW. In this study, the uncontrolled charging power sequence was reproduced by using the actual charged energy kWh and assuming the normal charging power of 6 kW.

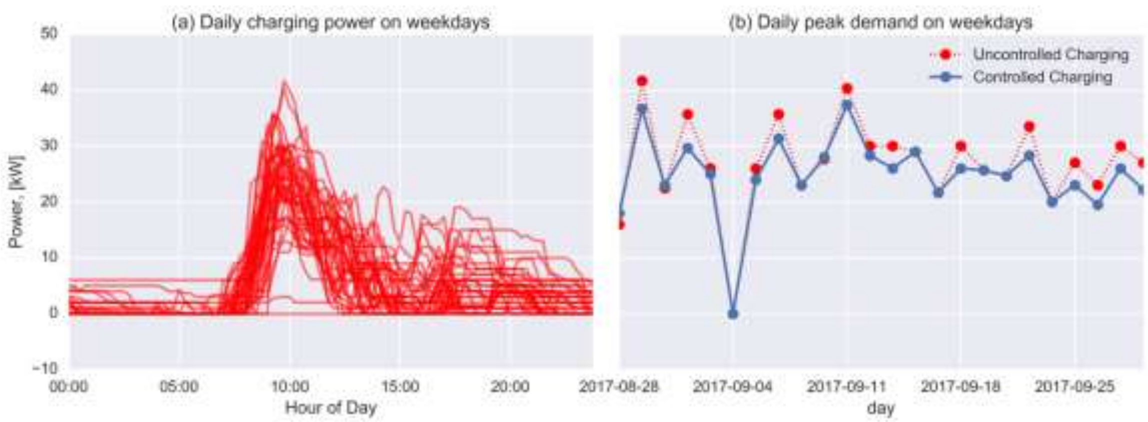
Figure 30: Charging Control of Public Electric Vehicles on September 26, 2017



Source: Lawrence Berkeley National Laboratory

Figure 31 (a) depicts the daily charging power profiles on weekdays during this period. The pattern is a very typical charging power profile in commercial public charging stations. The peak demand was observed in the early morning of the weekday. By implementing the smart charging control during pilot study participants' sessions, the monthly peak demand reduction was 4.4 kW between August 28, 2017 and September 28, 2017. Daily peak demand reductions ranged from 1 kW to 6 kW, depending mostly on the number of participant sessions. Daily peak demand reductions ranged from 3.8 percent to 17.9 percent with an average of 12.0 percent.

Figure 31: (a) Daily Charging Power on Weekdays and (b) Daily Peak Demand on Weekdays between August 28, 2017 and September 28, 2017



Source: Lawrence Berkeley National Laboratory

One or two pilot study participants joined in the smart charging control of charging sessions during this period. Throughout the summer period in 2017, the researchers observed the maximum value of the daily peak demand reductions on October 12, 2017 (Figure 32). The daily peak demand reduction varies from day to day, and was mostly affected by the number of participating charging sessions when the total charging demand was high.

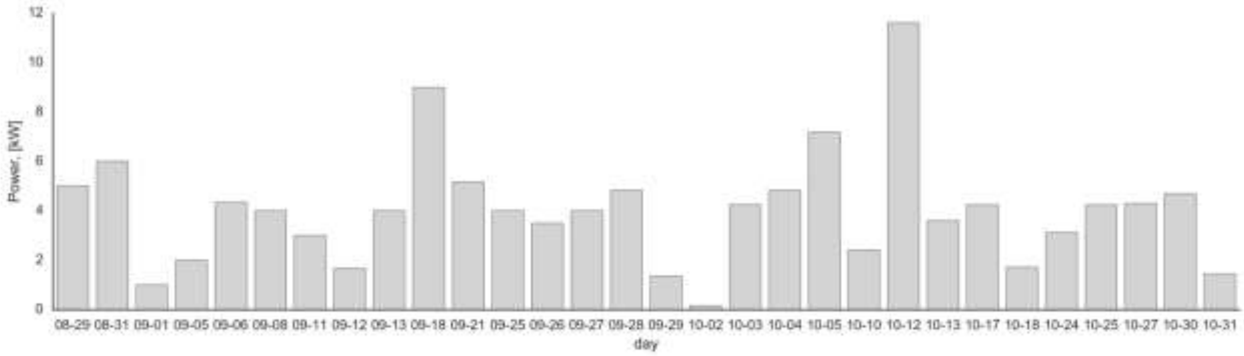
As discussed above, the performance of pilot study participants was evaluated by the number of participating sessions in the smart charging control, as well as the contribution to the daily peak demand reduction. Table 7 presents the participation rate summary of all the participants in the pilot study between August 29, 2017 and October 31, 2017. Nearly 50 percent of participants' charging sessions joined the smart charging control by providing their requested charging energy and departure time.

Table 7: Participation Rates in the Pilot Study between August 29-October 31, 2017

	#1	#2	#3	#4	#5	#6	#7	Sum
Charging Sessions	1	6	4	20	23	11	4	69
Participating Sessions	1	2	0	10	11	6	3	33
Participation Rate	100%	33%	0%	50%	48%	55%	75%	48%

Source: Lawrence Berkeley National Laboratory

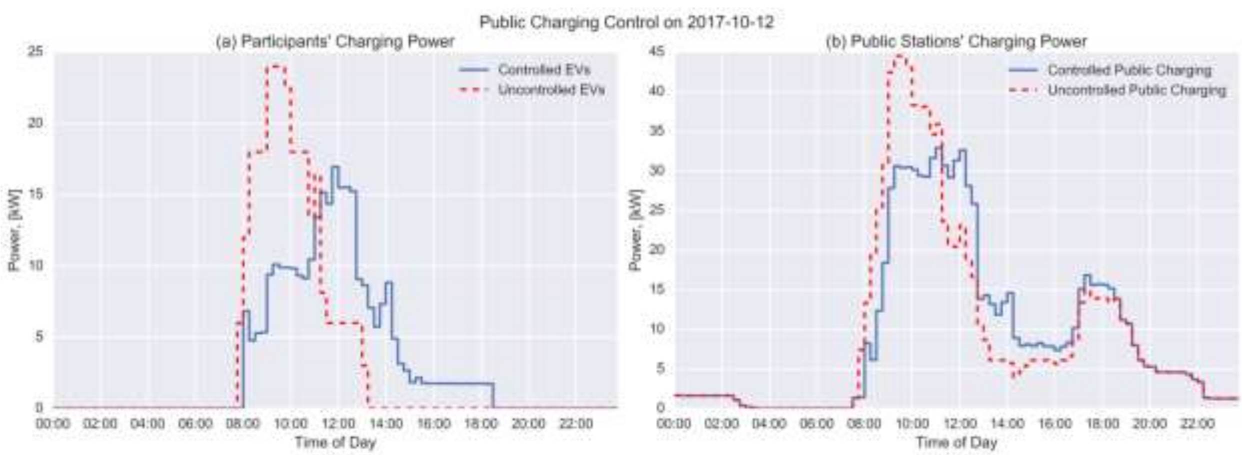
Figure 32: Daily Peak Demand Reductions between August 29, 2017 and October 31, 2017



Source: Lawrence Berkeley National Laboratory

On October 12, 2017, four participants were charging at the same time in the early morning and all of them responded to the request from the smart charging control with the charging energy and departure time. After implementing the optimal charging power schedule for each participant's charging session, the aggregated power demand was controlled to optimized charging schedules in blue from the original uncontrolled load profile in red, as shown in Figure 33. Considering only the pilot study participants, the daily peak demand was reduced by 7 kW as shown in Figure 33 (a). During the original peak period from 8 a.m. to 11 a.m., the peak demand was reduced from 24 kW to 10 kW. Figure 33 (b) depicts the total charging power of all the public charging stations which was decreased by 12 kW, about 27 percent of the original uncontrolled peak demand. This shows that the smart charging control system successfully reduces the charging power of public EVs.

Figure 33: Results of Charging Control for Public Electric Vehicles on October 12, 2017



Source: Lawrence Berkeley National Laboratory

Multiple Location Smart Charging

Considering the aggregation of EVs into the grid services on the electricity market, the smart charging control system was tested simultaneously in different locations. For this testing, the charging stations were located at three Alameda County operated sites, two in Oakland and one in San Leandro.

On October 31, 2017, three EVs were coordinated to optimally charge simultaneously at each of three different locations. Testing vehicles are presented in Table 8. As shown in Figure 34, three vehicles began charging at different times of the day.

Table 8: Testing Vehicles for Locational Based Scheduling Control

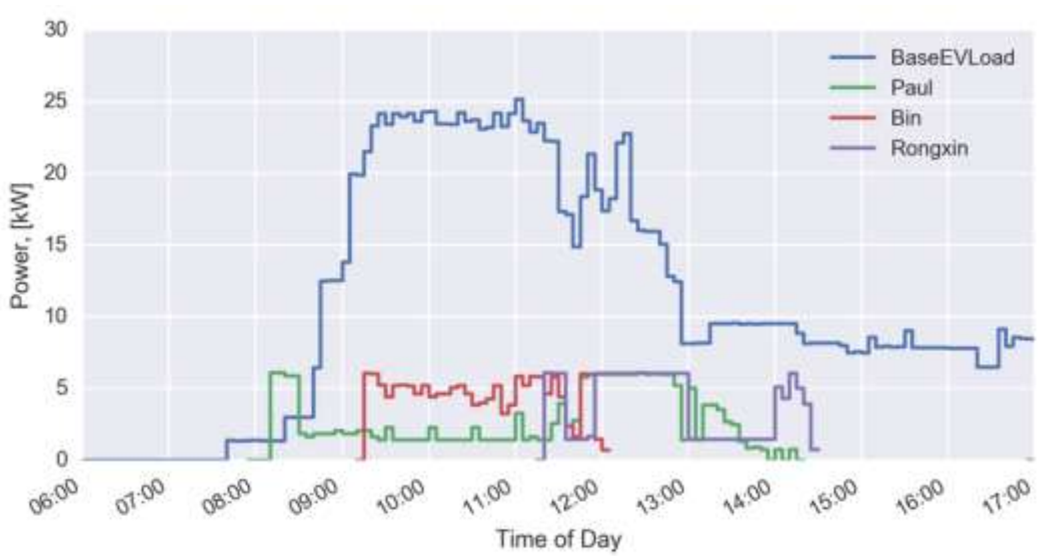
Participants	EV Model	Capacity (kWh)
# 1	2015 Nissan Leaf	24
# 2	2017 Nissan Leaf	30
# 3	2016 Nissan Leaf	24

Source: Lawrence Berkeley National Laboratory

Public Electric Vehicle Smart Charging Lessons Learned

Typically in the literature, the lower bound of charging power settings has been neglected in the optimization problem for achieving the optimal charging power sequence. In this study, charging power interruption was observed when the charging power setting was less than 1.5 kW. Frequent power interruptions may lead to the end of charging sessions earlier than expected. It can cause “range anxiety” for the driver of the charging controlled EV due to the unexpected delivery of less than expected charging energy.

Figure 34: Results of Locational Based Scheduling Control on October 31, 2017



Source: Lawrence Berkeley National Laboratory

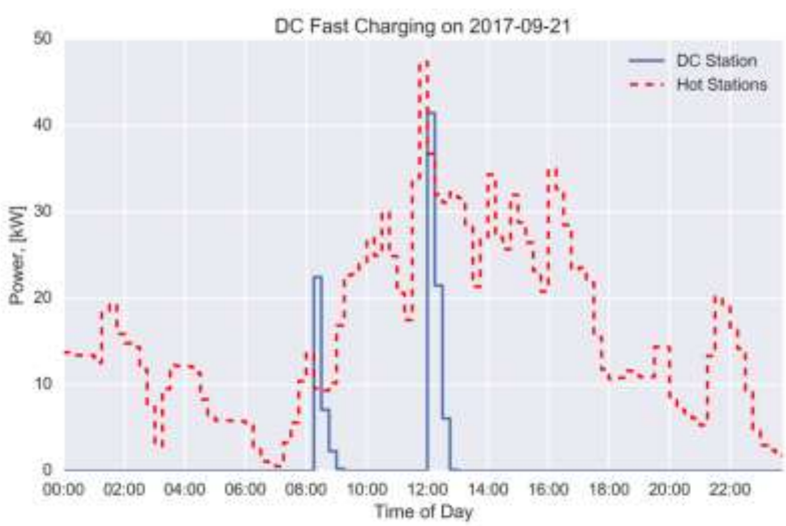
A top priority of a smart charging control system must be that the request of charging energy be guaranteed by the end of the charging session without any compromise of the charging request. In the smart charging control system developed here, a safety factor of 1.2 on the driver's submitted charging energy kWh was implemented to offset the difference between the scheduling power setting and the real charging power during the charging session. In this study, the charging activities of the pilot study participants were summarized into performance reports for each participant. The requests for smart charging control were fulfilled by either being fully charged by the end of the charging session or being charged with the requested charging energy. The goal of demand and cost savings under the TOU tariff was demonstrated by this smart charging control system.

Difficulties were encountered in recruiting and maintaining volunteers for study participation. Future studies of a similar nature would benefit from more knowledge and information on incentivizing human behavior with respect to public participation recruitment and retention.

Direct Current Fast Charging Smart Charging Results

The control strategy for managing the DCFC charging power spike by reducing concurrent fleet charging session demand was implemented starting September 10, 2017. Figure 35 shows the power demand of DCFC charging sessions (the blue solid line) and the aggregated power demand of concurrent fleet station sessions (the red dotted line). The power demand of the second DCFC charging session at 12 p.m. is more than 40 kW in the first 15 minutes.

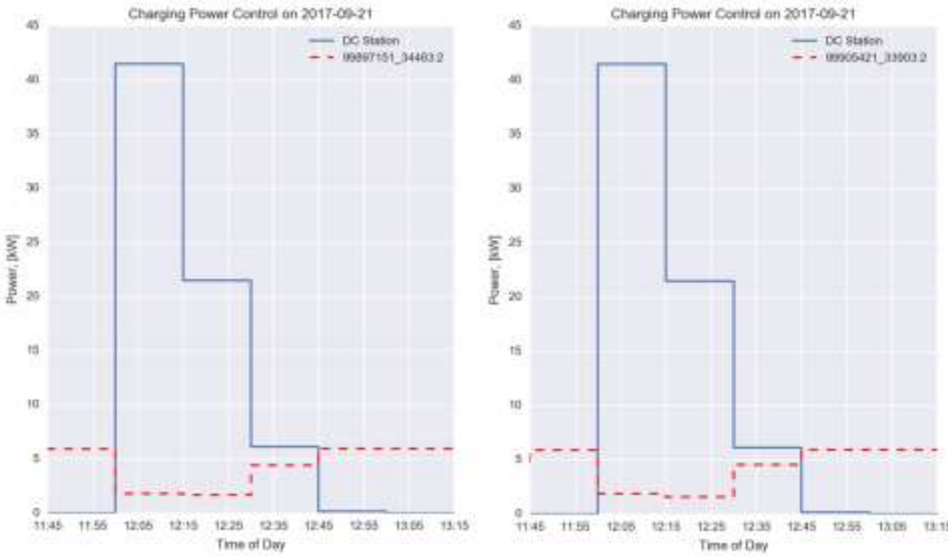
Figure 35: Direct Current Fast Charging on September 21, 2017



Source: Lawrence Berkeley National Laboratory

There were two concurrent fleet sessions in the active charging mode during the period of this DCFC charging session. Results presented in Figure 36 indicate that the control strategy was successfully implemented on the concurrent fleet sessions when the DCFC charging was on. The charging power of the fleet sessions was reset to 1.65 kW from the normal Level 2 charging power of 6 kW.

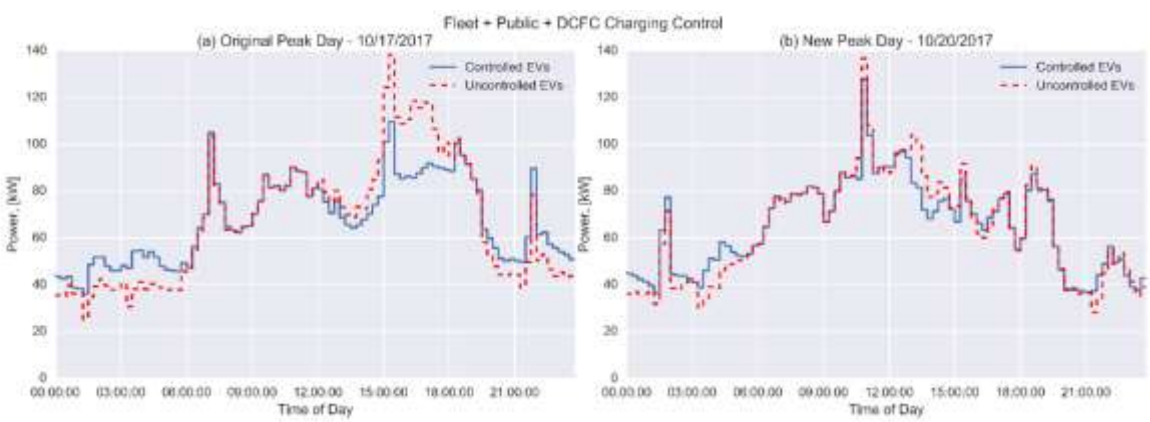
Figure 36: Power Limits on AlcoBase Charging Stations with Direct Current Fast Charging on September 21, 2017



Source: Lawrence Berkeley National Laboratory

In October 2017, the monthly peak demand was 127 kW, which was nearly 20kW lower than in September 2017. There were 76 DCFC charging sessions in September and 78 in October. As indicated in Figure 37, on the original peak day (October 17, 2017) when the DCFC session was on, there were 14 kW shed by limiting the charging power on the fleet charging stations. On the new peak day of October 20, 2017, 3.6 kW were shed.

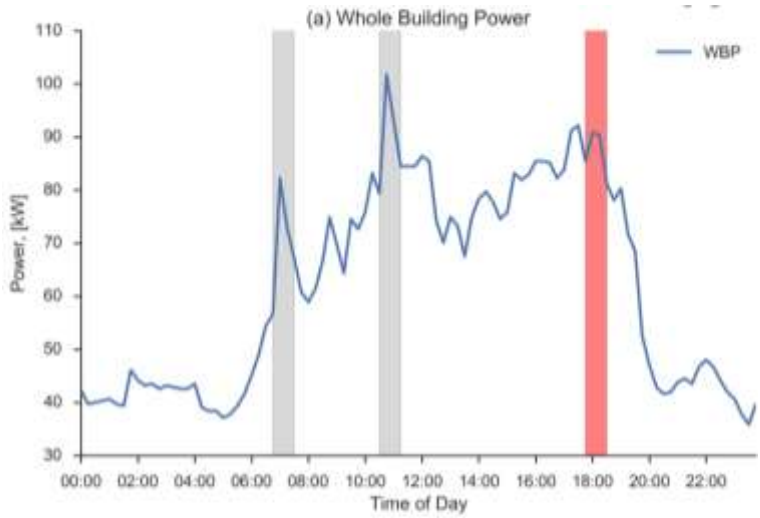
Figure 37: Smart Control of Direct Current Fast Charging Sessions in October 2017



Source: Lawrence Berkeley National Laboratory

The performance of the control strategy for managing the DC fast charging obviously depends on the number of active charging sessions on the fleet stations. Figure 38 depicts the whole building power with highlighted segments indicating DCFC charging sessions. There was no reduction of power demand for the DCFC charging sessions that occurred at 7 a.m. and 10:30 a.m. Active charging sessions on the controlled fleet stations at 6 p.m. led to a reduction of nearly 16 kW at the time of a DCFC session.

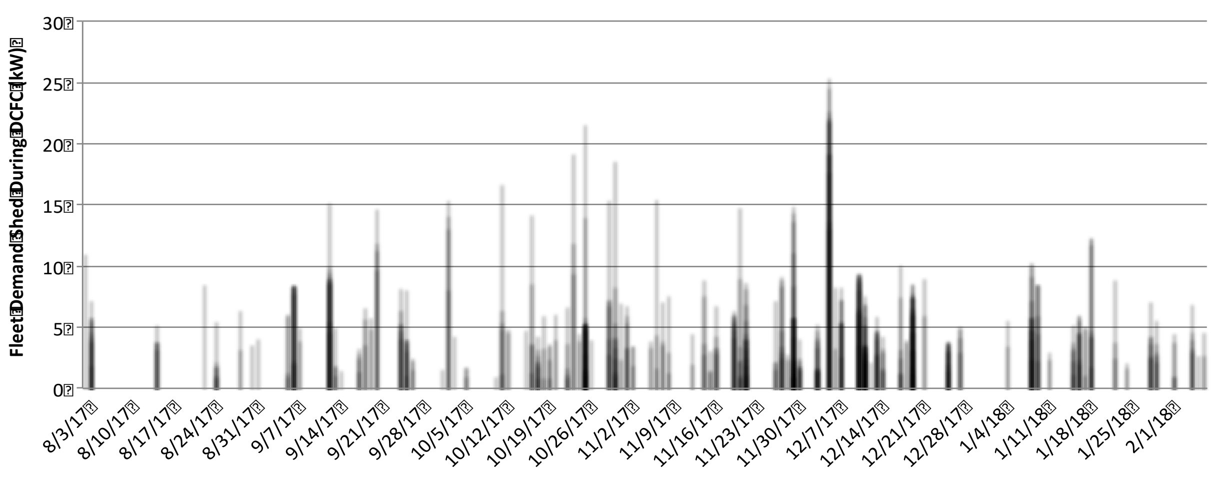
Figure 38: Whole Building Power with Highlighted Direct Current Fast Charging on October 3, 2017



Source: Lawrence Berkeley National Laboratory

To better understand the impact of the smart charging control for DCFC charging sessions, Figure 39 shows the summary of demand reductions from controlled charging stations from August 2017 to February 2018. The maximum power reduction is 26 kW, which is more than half of the DCFC charging maximum demand. The median value of the power reductions was 4.3 kW, which is equal to the kW shed from one active charging session. Overall, the deployed charging control of the controlled fleet stations successfully offset the power spike related to DCFC charging sessions.

Figure 39: Demand Reduction from Controlled Charging Stations During Direct Current Fast Charging Sessions



Source: Lawrence Berkeley National Laboratory

Smart Charging for Direct Current Fast Charging Lessons Learned

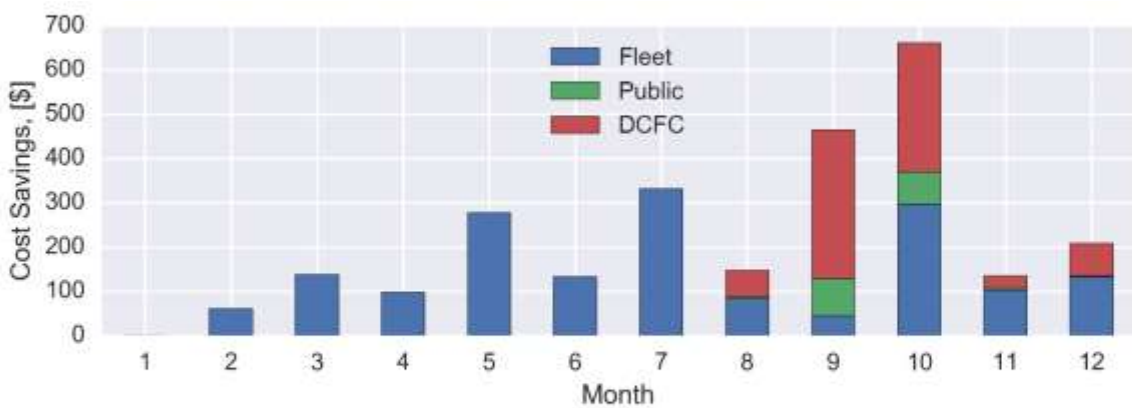
DCFC charging can contribute to significantly high energy and demand charges on the utility bill, especially when it is on during the on-peak period. Considering the operation of fleet EVs by Alameda County, it is recommended to limit the charging power on selected fleet charging stations when the DCFC charging is on. Such a short period of charging power limit does not have much effect on the charging sessions of fleet vehicles, because fleet vehicles usually get charged over long periods, and often overnight, in the garage. On the other hand, privately owned EVs are not suitable for such a control strategy due to the "range anxiety" that it could cause drivers.

Clearly, the performance of this control strategy for managing the power spike from DCFC charging in a short period varies along with the number of active charging sessions at the fleet stations. Each active charging session can easily contribute about 4.5 kW of power reduction to offset the DCFC demand spike.

Smart Charging Summary

In 2017, smart charging control strategies for fleet and DCFC were implemented in February and August separately. The primary period for public smart charging was from August to October. The total cost savings in 2017 was $2,651, which includes $1,697 for fleet vehicles, $169 for public vehicles, and $785 for DCFC (Figure 40).

Figure 40: Summary of Cost Savings from Fleet, Public, and Direct Current Fast Charging in 2017



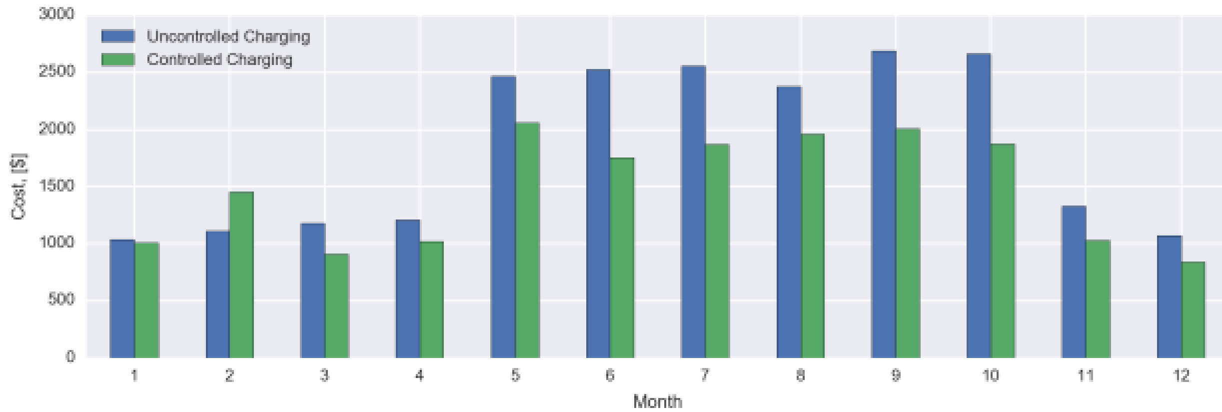
Source: Lawrence Berkeley National Laboratory

Fleet Electric Vehicles

In 2017, nearly 1,000 charging sessions were controlled to minimize the peak demand of fleet EVs, which represented about 25 percent of total fleet charging sessions. The average cost saving per session was about $1.80. In one week during a summer month, the peak demand during the on- and mid-peak periods was reduced by 10.7 kW and 13.3 kW, respectively.

When the controlled fleet sessions were the only electric load at the site, the cost savings from smart charging ranged from 15 percent to 30 percent (Figure 41).

Figure 41: Cost Savings Considering Only Smart Charged Fleet Sessions at AlCoPark Garage in 2017



Source: Lawrence Berkeley National Laboratory

Public Electric Vehicles

For the pilot study participants only, daily peak demand was reduced by 7.0 kW. During the original peak period from 8 a.m. to 11 a.m., peak demand was reduced from 24.2 kW to 10.0kW. The total charging power of all the public charging stations decreased by 12.0 kW, which is 26.7 percent of the original uncontrolled peak EV charging demand.

The controlled sessions for the pilot study participants represented 53.2 percent of their total charging sessions, while the controlled sessions for public participants represented 4.6 percent of their total sessions. Overall, the cost saving per participating session was $2.50 per session for the public charging (Figure 42).

Figure 42: Cost Savings Considering Only Smart Charged Public Sessions at AlCoPark Garage in August-December 2017

Source: Lawrence Berkeley National Laboratory

Direct Current Fast Charging

For DCFC charging, the maximum power reduction was 20 kW, which is nearly half of the DCFC charging power in the normal mode. The median value of the power reductions is 4.3 kW, which is equal to the kW shed from one active charging session (Figure 43).

Figure 43: Cost Savings Considering Only Smart Charged Direct Current Fast Charging Sessions at AlCoPark Garage in September-December 2017

Source: Lawrence Berkeley National Laboratory

CHAPTER 5: Market Opportunities for Electric Vehicles

Introduction

The primary goal of this project was to achieve lower operating costs by controlling EV charging for demand charge mitigation and to take advantage of time-of-use rates. In addition, new revenues will be enabled by controlling EV charging to offer grid services including demand response (DR) and ancillary services. LBNL performed simulations to evaluate the potential cost benefit of using controlled EV charging to enable the offering of grid services like demand response

Considering the complexity of the multiple energy markets and the real-world constraints of electric vehicles, LBNL selected multiple DR products in the retail and wholesale electricity markets as targets to integrate EVs. The researchers considered (1) the time-of-use (TOU) tariff that includes the energy charge and the demand charge, as well as the peak-day pricing (PDP) program; (2) the demand bidding program (DBP) in the retail electricity market; (3) the proxy demand resource (PDR) program; and (4) ancillary services on the wholesale energy market (Table 9). For markets with a minimal participation threshold, LBNL adapted the methods used in unit commitment with auxiliary integer variables to indicate whether or not the aggregated resources will be engaged in the markets. In addition, for markets that require a minimal commitment length, LBNL brought in auxiliary binary decision variables with specific constraints to guarantee the commitment period is larger than the minimal threshold if the resource is scheduled to participate in the market. Specifically, for frequency regulation markets, LBNL adapted the modeling and evaluation approaches in (DeForest, MacDonald, & Black, 2018), inspired by the real-world regulation signals collected from California energy markets.

Table 9: Demand Response Products in the Retail and Wholesale Electricity Markets

Electricity Markets	Programs/Products
Retail	Peak Day Pricing
	Demand Bidding Program
Wholesale	Proxy Demand Resource
	Frequency Regulation

Source: Lawrence Berkeley National Laboratory

California Demand Response Markets

The California Independent System Operator (CAISO) offers wholesale market aggregators the PDR product that enables them to offer DR resource directly into the wholesale energy and ancillary services market and allows non-generator resources to bid their 15-minute capacity into the regulation market as well. The PDR resources can bid economically into the following markets: (1) day-ahead energy market with the minimum load curtailment of 100 kW; (2) day-ahead and real-time non-spinning reserve market with the minimum load curtailment of 500 kW; and (3) 5-minute real-time energy market. Additionally, smaller loads may be aggregated together to achieve the minimum load curtailment. PDR is only a load curtailment product, which is not enabled for load increase, so negative DR energy management (for example, the use of battery discharge for PDR) is set to zero for the settlement of PDR.

Simulation Structure Overview

In LBNL's simulation, EV load was modeled as deferrable load that can be shifted to different time windows to achieve various grid objectives in different energy markets. Accordingly, optimization-based strategies were developed that allow the EV fleet manager to coordinate the integration of EVs with multiple different market strategies to minimize the energy cost for serving the transportation required from the fleet EVs. The aggregate EV controller would retrieve day-ahead pricing information from multiple DR markets from CAISO servers and collect the EV usage info, including energy demand and itineraries, from individual EV drivers. This communication has already been enabled in the demonstration project. During the next-day operation, each EV follows the day-ahead schedule in each time step to fulfill its own energy demand. For all DR markets modeled in this project, the pricing information can be obtained a day ahead, thus no online operations are needed. For the real-time regulation signal, LBNL used the utilization factors to model its impact.

Nomenclature

The important parameters and variables in the simulation are:

Indices and Sets

D, d	days in each month, day index
D_{PDP}, d_{PDP}	PDP event days, PDP day index
T, t	time steps for one single day, time index
T_{PDP}, t_{PDP}	time steps during PDP event, time index in PDP days
T_P	time steps in peak periods;
T_{PP}	time steps in part-peak periods;
T_M	time steps in global maximal periods;
I, i	demand charge periods including peak, part-peak and global maximal periods, index of demand charge periods

T_i	time steps for demand charge period i
$N_p^d(t)$	plugged-in vehicles at time t on day d

Parameters and Variables

$b_n^d(t)$	binary charging indicator for vehicle n
$p_n^d(t)$	charging power for vehicle n at time t on day d
$\underline{p}$	minimal effective charging power
$\overline{p}$	maximal effective charging power
$e_n^d(t)$	energy charged to vehicle n by time t on day d
$e_{n,req}^d$	energy requested by vehicle n on day d
$t_n^{d,a}$	arrival time of vehicle n on day d
$t_n^{d,l}$	departure time of vehicle n on day d
$e_{n,d}^{+/-}(t)$	fastest/slowest accumulated energy boundaries of vehicle n by time t on day d
$E_d^{+/-}(t)$	fastest/slowest accumulated energy boundaries of the virtual battery by time t on day d
$P^d(t)$	aggregated charging power by time t on day d
$L^d(t)$	baseload at time t on day d
η_c	charging efficiency
$\lambda(t)$	energy charge rate for time t
ω_i	demand charge rate for demand period i
P_{PDP}^{CR}	capacity reserve value for PDP policy
λ_{PDP}	energy charge rate during PDP events
C_{EC}	monthly energy charge cost
C_{DC}	monthly demand charge cost
π_{PDP}^p	PDP credit rate for peak demand period
π_{PDP}^m	PDP credit rate for global-max demand period
R_{PDP}^m	PDP credit for global-max demand periods
R_{PDP}^p	PDP credit for peak demand periods
C_{PDP}	monthly energy charge during PDP events
R_{AS}	monthly revenue from ancillary service market

$\pi_{up}^{d}(t)$	regulation up price at time t on day d
$\pi_{down}^{d}(t)$	regulation down price at time t on day d
$R_{up}^{d}(t)$	regulation-up bid at time t on day d
$R_{down}^{d}(t)$	regulation-down bid at time t on day d
ρ_{up}	utilization factor of regulation up signals
ρ_{down}	utilization factor of regulation down signals
$B^{d}(t)$	aggregate power baseline at time t on day d
$b_{agg}^{d,B/P}(t)$	binary indicator for aggregate baseline/actual power at time t on day d
$b_{agg}^{d,ru/rd}(t)$	binary indicator for aggregate regulation up/down power at time t on day d
$b_{agg}^{d,bu/bd}(t)$	binary indicator for aggregate power with full up/down signals at time t on day d
$b_{down}^{d}(t)$	binary regulation-down indicator at time t
$\underline{R}_{up/down}$	min. threshold in regulation up/down markets
R_{PDR}	Revenue in PDR markets
$R_{sell}^{d}(t)$	Virtual sell power at time t on day d
$\pi_{pdr}^{d}(t)$	PDR market price at time t on day d
$b_{agg}^{sell}(t)$	binary indicator for sell power in PDR market
$\underline{R}_{sell}^{PDR}$	min. power threshold on PDR market
R_{DBP}	Revenue from DBP market
π_{DBP}	credit rate on DBP market
$R_{rdc}^{d}(t)$	reduced power due to DBP events at time t on day d
$b_{DBP}^{d}(t)$	binary indicator for DBP power reduction at time t on day d

Modeling Electric Vehicles in Multiple California Demand Response Markets

Aggregation of Electric Vehicles

For each individual vehicle n on day d, the following constraints should be satisfied.

$$b_n^d(t) \cdot \underline{p} \leq p_n^d(t) \leq b_n^d(t) \cdot \bar{p} \tag{1}$$

$$e_n^d(t+1) = e_n^d(t) + p_n^d(t) \cdot \eta_c \cdot \Delta t \tag{2}$$

$$e_n^d\left(t_n^{d,l}\right) \geq e_{n,req}^d \tag{3}$$

$b_n^d(t)$ in equation (1) is the indicator of whether vehicle n is charging at time t. Note that the feasible charging range is not continuous so as to model the real-world EV chargers. When $b_n^d(t)$ is set to 0, both the left- and right-hand sides are 0, constraining the charging power to 0, that is, the inactive state. For the active state, the charging power threshold $\overline{p}$, i.e. minimal charging power, is set to 1.5 kW, which corresponds to the limit of the chargers used in the demonstration project. Equation (2) indicates the accrual of energy consumption for each vehicle and the energy consumption value at the time of charging session finish time t_n^f, i.e. $e_n^d(t_n^l)$, should be larger than the requested amount $e_{n,req}^d$. Note that energy requests for vehicles are collected by a driver-charger interface.

To reduce the number of decision variables in the optimization problem, modeling approaches from (Zhang, Hu, Xu, & Song, 2017) were adapted to aggregate numerous individual EVs as one single virtual battery with power and energy boundaries, hereby improving the computational efficiency. According to this approach, any trajectory that falls between the power and energy boundaries can be achieved by controlling each EV's charging power. The approach is summarized as follows:

$$E_d^{+/-}(t) = \sum\nolimits_{n \in N_p(t)} e_{n,d}^{+/-}(t) \ , t \in [0, T] \tag{4}$$

$$E_d^-(t) \leq \sum_{\tau=0}^{t} P^d(\tau) \cdot \Delta t \leq E_d^+(t), \qquad \forall t \in [0, T] \tag{5}$$

$$\overline{P}^d = \sum\nolimits_{n \in N_p^d(t)} \overline{p} \cdot \eta_c \tag{6}$$

$$b_{agg}^d \cdot \underline{p} \leq P(t) \leq b_{agg}^d \cdot \overline{P}^d, \qquad \forall t \in [0, T] \tag{7}$$

The aggregate energy boundaries, i.e. $E_d^{+/-}(t)$, are obtained by summing up $e_{n,d}^+(t)$, which is the accumulated energy from the as-fast-as-possible charging pattern, and $e_{n,d}^-(t)$, which is from the as-late-as-possible charging pattern. In addition, the total power consumption value should be lower than the aggregated power from all available vehicles at time t. Discontinuity of the aggregated power is also modeled, similar to equation (1). The optimal power consumption profiles for day-ahead operations can be used as the reference for EVs to follow during the real-time operations in distributed and asynchronous fashions, which are, however, not the focus of this chapter.

Time-of-Use Tariff Structure

For commercial sites in California TOU markets, two categories of costs are generally applied to customers' bills: energy charge and demand charge. Energy charges are calculated by multiplying the amount of electricity used per time period, measured in kilowatt-hours (kWh), by the per-kWh rate for that time period. The demand charge is calculated by multiplying the maximum load measurement in each demand period by the corresponding demand charge rate, in $/kW. Thus, the total monthly cost of energy charge is modeled by equation (8), where costs of energy consumption in different time periods are all included. Equation (9) models the total monthly demand charges, where I denotes the set of the demand charge periods. In the case of the E-19 tariff in PG&E territory, there are three demand charge periods for summer months (peak, part-peak, and any-time max periods) and two for winter months (part-peak and any-time max periods).

$$C_{EC} = \sum\nolimits_{d \in D} \sum\nolimits_{t \in T} (L^d(t) + \sum_{n=1}^{N_p^d(t)} P^d(t)) \cdot \Delta t \cdot \lambda(t) \tag{8}$$

$$C_{DC} = \sum_{T_i \in \{T_p, T_{pp}, T_M\}} \max_{\substack{t \in T_i \\ d \in D}} \left(L^d(t) + \sum_{n}^{N_p^d(t)} P^d(t) \right) \cdot \omega_i \tag{9}$$

Thus, to minimize the monthly energy bills by considering only the energy charge and demand charges, a deterministic optimization problem is formulated as:

Problem 1 – TOU charges (energy charge + demand charge)

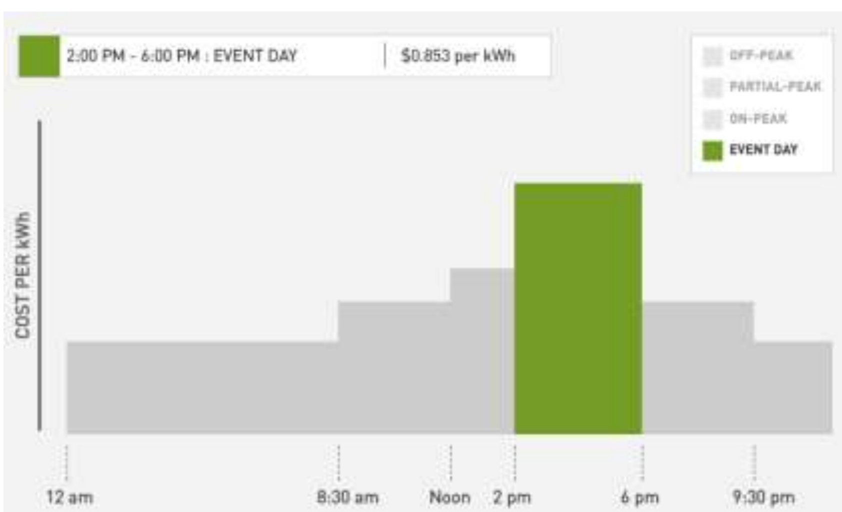
Objective: $minimize\ (C_{EC} + C_{DC})$

Subject to: (1)-(9)

Integration with Peak Day Pricing Plan

Peak Day Pricing (Figure 44) is an optional rate that offers businesses a discount on regular summer electricity rates in exchange for higher prices during 9 to 15 peak pricing event days per year which typically occur on the hottest days of the summer (PG&E defines summer as May 1 to October 31). When utilities observe or anticipate high wholesale market prices, high demand, or a power system emergency, they call critical events during a specified time (for example, 2 p.m. to 6 p.m. on summer weekdays). The price for electricity during these times is substantially higher.

Figure 44: Peak Day Pricing: Event Day Rates



Note: Based on A1 rates per kWh as of July 1, 2017.

Source: Lawrence Berkeley National Laboratory

The customer must submit a capacity reservation value, that is, P_{PDP}^{CR}, to the load-serving entity, in this case the utility. The demand peaks in different demand periods that exceed the capacity reservation value will be protected from the demand charges by the PDP policy, that is, credits will be billed to customers for the exceeding amount. This policy is modeled by equation (10) and (11). However, the total energy consumption in kWh below P_{PDP}^{CR} during PDP events will be billed with PDP energy charge rate λ_{PDP}, which is modeled by equation (12). The optimal EV charging problem with the PDP market participation is summarized in the problem 2.

$$R_{PDP}^{p} = \pi_{PDP}^{p} \cdot (\max_{\substack{d \in D_{PDP} \\ t \in T_{PDP} \cap T_P}} \left(L^d(t) + \sum\nolimits_{n \in N_p^d(t)} p_n^d(t) \right) \tag{10}$$

$$R_{PDP}^{m} = \pi_{PDP}^{m} \cdot (\max_{\substack{d \in D_{PDP} \\ t \in T_{PDP} \cap T_M}} \left(L^d(t) + \sum\nolimits_{n \in N_p^d(t)} p_n^d(t) \right) \tag{11}$$

$$C_{PDP} = \lambda_{PDP} \cdot \sum\nolimits_{d \in D_{PDP}} \sum\nolimits_{t \in T_{PDP}} \max_{\substack{d \in D_{PDP} \\ t \in T_{PDP}}} (L^d(t) + \sum\nolimits_{N_p^d(t)} p_n^d(t) - P_{PDP}^{CR}, 0) \cdot \Delta t \tag{12}$$

Problem 2 – TOU charges with PDP integration

Objective: $minimize\ (C_{EC} + C_{DC} - R_{PDP}^{p} - R_{PDP}^{m} + C_{PDP})$

Subject to: (1) - (12)

Integration with Ancillary Service Market

To achieve instantaneous balance between the supply and demand sides of the electricity transmission system, ancillary services can be used by calling services from various grid components, not only traditional electricity generators but also demand-side distributed energy resources. A regulation up/down market is representative of ancillary service markets. EVs with the capability to follow the up and down regulation signals in a short period of time can be coordinated to serve as effective and reliable resources to provide regulation services. Based on the formulation of Problem 1, the EV integration with regulation market participation was modeled as:

$$R_{AS} = \sum\nolimits_{d \in D} \sum\nolimits_{t \in T} (R_{up}^d(t) \cdot \pi_{up}^d(t) + R_{down}^d(t) \cdot \pi_{down}^d(t)) \cdot \Delta t \tag{13}$$

$$P^d(t) = B^d(t) + \rho_{up} \cdot R_{up}^d(t) + \rho_{down} \cdot R_{down}^d(t) \tag{14}$$

$$b_{agg}^{d,B}(t) \cdot \underline{p} \leq B^d(t) \leq b_{agg}^{d,B}(t) \cdot \overline{P}^{\mathrm{d}} \tag{15}$$

$$b_{agg}^{d,P}(t) \cdot \underline{p} \leq P^d(t) \leq b_{agg}^{d,P}(t) \cdot \overline{P}^{\mathrm{d}} \tag{16}$$

$$E_d^-(t) \leq \sum\nolimits_{t_0}^{t} P^d(\tau) \cdot \Delta t \leq E_d^+(t) \tag{17}$$

$$E_d^-(t) \leq \sum\nolimits_{t_0}^{t} B^d(\tau) \cdot \Delta t \leq E_d^+(t) \tag{18}$$

$$b_{agg}^{d,B}(t) \cdot \underline{R}_{down} \leq R_{down}^d(t) \leq b_{agg}^{d,B}(t) \cdot \overline{P}^{\mathrm{d}} \tag{19}$$

$$b_{agg}^{d,ru}(t) \cdot \underline{R}_{up} \leq R_{up}^{d}(t) \leq b_{agg}^{d,ru}(t) \cdot \overline{P}^{\mathrm{d}} \quad (20)$$

$$b_{agg}^{d,bd}(t) \cdot \underline{p} \leq B_d(t) + R_d(t) \leq b_{agg}^{d,bd}(t) \cdot \overline{P}^{\mathrm{d}} \quad (21)$$

$$b_{agg}^{d,bu}(t) \cdot \underline{p} \leq B_d(t) - R_u(t) \leq b_{agg}^{d,bu}(t) \cdot \overline{P}^{\mathrm{d}} \quad (22)$$

Equation (13) shows the expression for calculating the total revenue from day-ahead frequency regulation markets. The revenue consists of the regulation-up capacity payment and regulation-down capacity payment. Unlike the modeling approaches in previous research where day-ahead commitments can be violated with penalties, LBNL's simulation did not violate the commitment in any circumstances due to the performance regulations in California ancillary service markets.

Because of the non-continuity property of power boundaries, auxiliary binary decision variables are defined to indicate the options to participate in the regulation up and down markets. Given regulation signals from CAISO, an aggregate EV fleet, for example, will follow the signals, that is, increase or decrease the aggregated power consumption of the EVs. The revenue is calculated based on the day-ahead bids (the committed regulation up and down capacities) rather than the actual increased or decreased power consumption following real-world regulation signals, indicated by equation (14). The negative (up), ρ_{up}, and positive (down), ρ_{down}, utilization factors represent the fraction of the committed regulation dispatched by the CAISO control signal. Actual utilization factors collected during a real-world demonstration project at Los Angeles Air Force Base were used in the simulations presented here. The baseline aggregate power $B^d(t)$ is the original power consumption profile assuming no regulation signals, while $P^d(t)$ is the actual power profile in equation (15) – (18). Here, $B^d(t)$ is a decision variable. Equation (19), (20) model the constraints that the aggregate fleets can participate in the regulation up or down markets, or choose to stay out of the markets. We also assume that the aggregated EV fleet can follow all regulation signals, i.e. the actual power consumption should always stay in the power boundaries, which is modeled by equations (21) and (22).

Note that the aggregator can make regulation up and down bids for the same time periods, even if one of them will not be called during implementation, but still getting benefits for the bids. Additionally, the actual aggregate power and the aggregated baseline profiles should both satisfy the aggregate energy and power constraints, modeled in equation (4) - (7). The problem is formulated as:

Problem 3 – TOU charges with regulation markets

Objective: $minimize\ C_{EC} + C_{DC} - R_{AS}$

Subject to: (1) - (9), (13) – (22)

Modeling of Proxy Demand Resource Market

Aggregated EVs can also participate in the PDR market, in which the fleet EVs are treated as a virtual battery with flexibility to "sell" the power in the PDR market. For EVs with vehicle-to-grid (V2G) capabilities, "sell" operations can be achieved by discharging the vehicle batteries, while for V1G,[2] “selling” of power would be achieved by reducing the aggregate power consumption relative to a power consumption baseline. The model is presented as follows:

$$R_{PDR} = \sum_{d \in D} \sum_{t \in T} R_{sell}^{d}(t) \cdot \pi_{pdr}^{d}(t) \cdot \Delta t \tag{23}$$

$$M_s \cdot \left(1 - b_{agg}^{PDR}(t)\right) \leq P^d(t) - B^d(t) + R_{sell}^{d}(t) \leq M_b \cdot (1 - b_{agg}^{PDR}(t)) \tag{24}$$

$$b_{agg}^{sell}(t) \cdot \underline{R}_{sell}^{PDR} \leq P_n^d(t) \leq b_{agg}^{sell}(t) \cdot \overline{P}^{d} \tag{25}$$

The revenue from the PDR market is a product of the virtual sell power, i.e. $R_{sell}^{d}(t)$, multiplied by the corresponding PDR market prices, i.e. $\pi_{pdr}^{d}(t)$ in equation (23). The baseline power consumption $B_n^d(t)$, is typically the averaged value of a number of previous days, thus here we model it as a known profile before optimization. In reality, PDR market participation has a requirement of a minimal threshold for virtual sell power, i.e. $\underline{R}_{sell}^{PDR}$ in equation (25). In equation (24), $b_{agg}^{PDR}(t)$ is the binary indicator of whether the fleets are participating in the PDR market. When $b_{agg}^{PDR}(t) = 1$, i.e. participating, equation (24) is reduced to:

$$P^d(t) = B^d(t) - R_{sell}^{d}(t) \tag{26}$$

where the actual power consumption value $P_n^d(t)$ equals the baseline power $B^d(t)$ minus the virtual sell power $R_{sell}^{d}(t)$. When $b_{agg}^{PDR}(t) = 0$, indicating no participation, equation (17) evolves to:

$$M_s \leq P^d(t) - B^d(t) + R_{sell}^{d}(t) \leq M_b \tag{27}$$

where M_s is a sufficiently small number and M_b is a sufficiently big number. Equation (27) remains true for all cases, making it a redundant constraint in the optimization problem, which can be effectively handled by current solvers with mixed-integer capabilities. In addition, to model the consecutive engagement constraint, some numerical approaches are applied as shown in equation (28) and (29),

$$b_c(t_0) = b_{agg}^{PDR}(t_0) \tag{28}$$

$$b_c(t) \leq 1 - b_{agg}^{PDR}(t - \Delta t) \tag{29}$$

$$b_c(t) \leq b_{agg}^{PDR}(t) \tag{30}$$

$$b_c(t) \geq b_{agg}^{PDR}(t) - b_{agg}^{PDR}(t - \Delta t), \ \forall t \in T \tag{31}$$

$$\sum_{\tau = t}^{\min(t + N_c - 1, T)} b_{agg}^{PDR}(t) - N_c \geq -N_b \cdot \left(1 - sc(t)\right), \forall t \in T \tag{32}$$

An auxiliary binary decision variable, i.e. $b_c(t)$, is utilized to model the consecutive participation constraint. $b_c(t) = 1$ indicates the beginning of a new block of consecutive participation at t. Equations (28) – (32) guarantee the number of consecutive participating time steps is greater or

[2] V1G is unidirectional power flow into a battery with no discharge of the battery to the grid, in contrast to V2G which is bidirectional power flow in and out of the battery.

equal to N_c. Incorporating binary decision variables into the optimization problems results in a mixed-integer programming problem, where sophisticated numerical solvers are needed. With PDR market integration, the overall problem is formulated as follows:

Problem 4 - TOU charges with PDR market participation

Objective: $minimize\ C_{EC} + C_{DC} - R_{PDR}$

Subject to: (1) - (9), (23) - (32)

Modeling of Demand Bidding Program

To increase system reliability, some utility companies are paying additional incentives to industrial, commercial, or agricultural customers to reduce their energy consumption during certain times. An example is PG&E's DBP. DBP events are dispatched in day-ahead operations, so pre-planning is necessary for optimizing the benefits. The modeling approaches for DBP markets are very similar to those for PDR market, except that a fixed credit ($/kW) is used to calculate the revenues. Aggregated EVs can be utilized as valuable resources in response to DBP events following the above virtual battery modeling approaches.

$$R_{DBP} = \pi_{DBP} \cdot \sum\nolimits_{d \in D} \sum\nolimits_{t \in T} R_{rdc}^{d}(t) \cdot \Delta t \tag{33}$$

$$b_{DBP}^{d}(t) \cdot \underline{R}_{DBP} \leq P^{d}(t) \leq b_{DBP}^{d}(t) \cdot \overline{P} \tag{34}$$

Note that there are also consecutive participation requirements and a minimal power reduction requirement, thus the constraints for the PDR market, i.e. equation (23) – (32) are also valid for DBP. The problem is defined as follows:

Problem 5 - TOU charges with DBP market participation

Objective: $minimize\ C_{EC} + C_{DC} - R_{DBP}$

Subject to: (1) - (9), (23) - (34)

Results and discussion

Actual Electric Vehicle Charging Profiles, Electric Utility Rate, and Ancillary Services Regulation Prices

The real-world datasets of public and fleet EV charging at the AlCoPark Garage from 2013-2017, including the whole building demand from the PG&E electric meter, were collected and used for the simulations presented and discussed below. The dataset properties are displayed in Table 10.

Table 10: Dataset of Charging Session in the Study

Number of Sessions	Number of EVSEs	First Session Date	Last Session Date
20,363	25	3/15/2013	9/7/2017

Source: Lawrence Berkeley National Laboratory

The demonstration site is under the PG&E E-19 tariff with energy and demand rates shown in Table 11. Ancillary service regulation up and down day ahead prices were collected from CAISO's Open Access Same-time Information System for 1/1/15 to 12/31/16 (CAISO, n.d.).

Table 11: Pacific Gas and Electric Company E-19 Demand Charge and Energy Charge Rates

Demand Charges	**$/kW**	**Time Period**
Maximum Peak Demand Summer	$18.74	12:00 p.m.-6:00 p.m.
Maximum Part-Peak Demand Summer	$5.23	8:30 a.m.-12:00 p.m. and 6:00 p.m.-9:30 p.m.
Maximum Demand Summer	$17.33	Any time
Maximum Part-Peak Demand Winter	$0.13	8:30 a.m.-9:30 p.m.
Maximum Demand Winter	$17.33	Any time
Energy Charges	**$/kW**	**Time Period**
Peak Summer	$0.14726	12:00 p.m.-6:00 p.m.
Part-Peak Summer	$0.10714	8:30 a.m.-12:00 p.m. and 6:00 p.m.-9:30 p.m.
Off-Peak Summer	$0.08057	Any time
Part-Peak Winter	$0.10166	8:30 a.m.-9:30 p.m.
Off-Peak Winter	$0.08717	Any time

Source: Pacific Gas and Electric Company, 2016

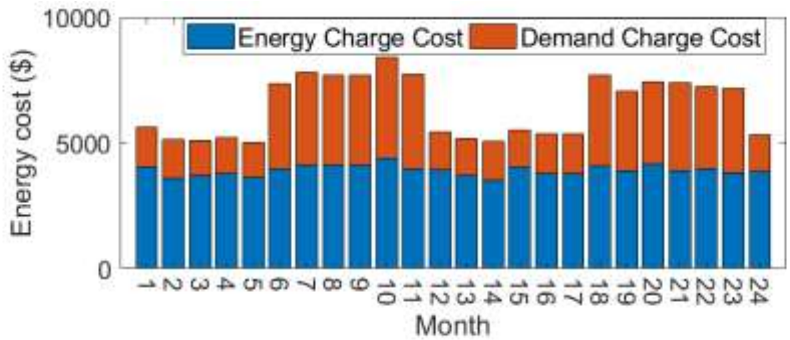
Simulation Results

Results of optimizations of EVs in the demand response programs and ancillary service markets described above are presented here. The first example optimizes charging schedules solely to minimize electric TOU costs. The second example optimizes to minimize TOU costs and maximize ancillary service regulation revenue.

First, the load shifting and cost reduction effects of smart charging programs under only TOU prices are presented. As shown in Table 11 above, the energy charge and demand charge rates in winter are lower than those in summer. As a result, AlCoPark Garage's actual total monthly costs for energy charges in winter were slightly lower than those in summer, indicated by the blue bars in Figure 45, and the total monthly demand charges are considerably lower than those of summer, indicated by the orange bars in Figure 45.

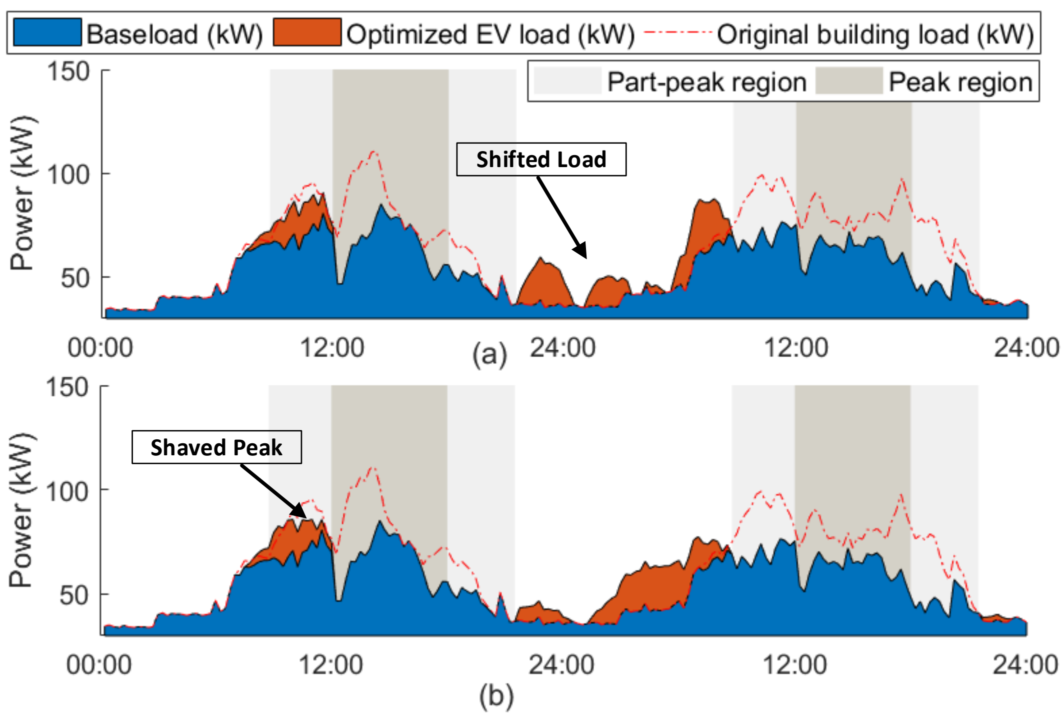
Since the demand charge is calculated by the monthly peak demand multiplied by the corresponding demand charge rate, the smart charging program has a tendency to reduce the monthly peaks in multiple demand windows. For instance, the load profile of the day with the maximum monthly demand in June 2016 is shown in Figure 46. The EV load profile optimized only to minimize energy charges is shown in upper figure (a). The EV load profile optimized to minimize both energy and demand charges is shown in lower figure (b), and highlights the flatter demand during the peak 12 p.m. to 6 p.m. period.

Figure 45: Actual Total Monthly Cost of Energy and Demand Charges for AlCoPark Garage from January 2015 to December 2016



Source: Lawrence Berkeley National Laboratory

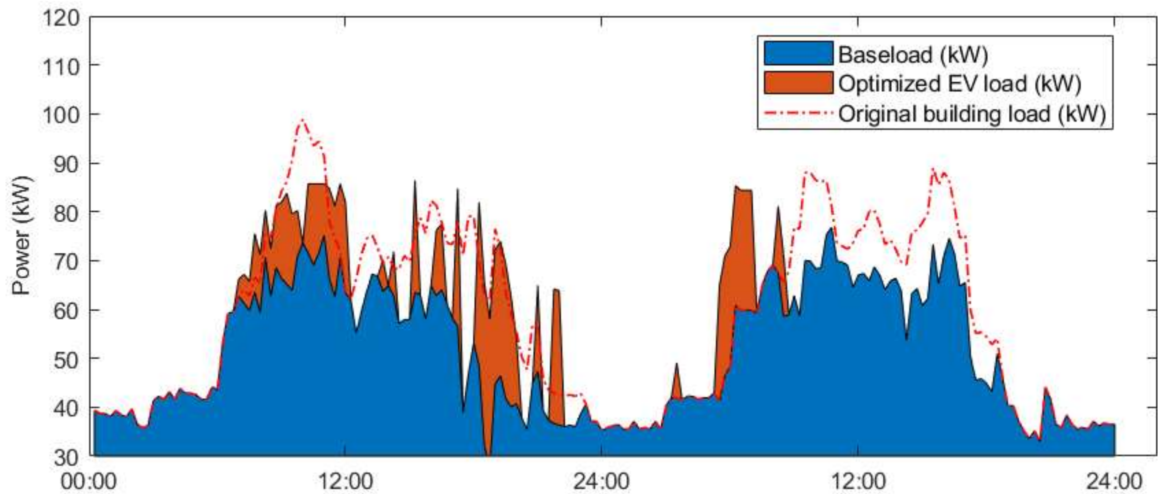
Figure 46: Example Smart Charge Electric Vehicle Load Shifting to Minimize Electric Costs on June 6, 2016



Source: Lawrence Berkeley National Laboratory

To investigate the impact of ancillary service market integration, an additional option in the simulated smart charging program was added to allow the EV fleet to modify the aggregate power consumption profile in response to the regulation up and down prices from the CAISO ancillary services market (problem 4 defined in the previous section). As shown in Figure 47, the EV load profile becomes spikier supporting the ancillary service market participation because the optimization tends to increase or decrease the power consumption when a high regulation up/down price is anticipated. However, with the possibility that increased EV charging load may cause to create new demand peaks, herein increasing the demand charges, the optimization has to evaluate the trade-off globally on a monthly basis. Illustrated by Figure 47, the adjusted power consumption profiles due to regulation market participation are constrained so as not to exceed the monthly demand peaks set by the TOU-based optimization.

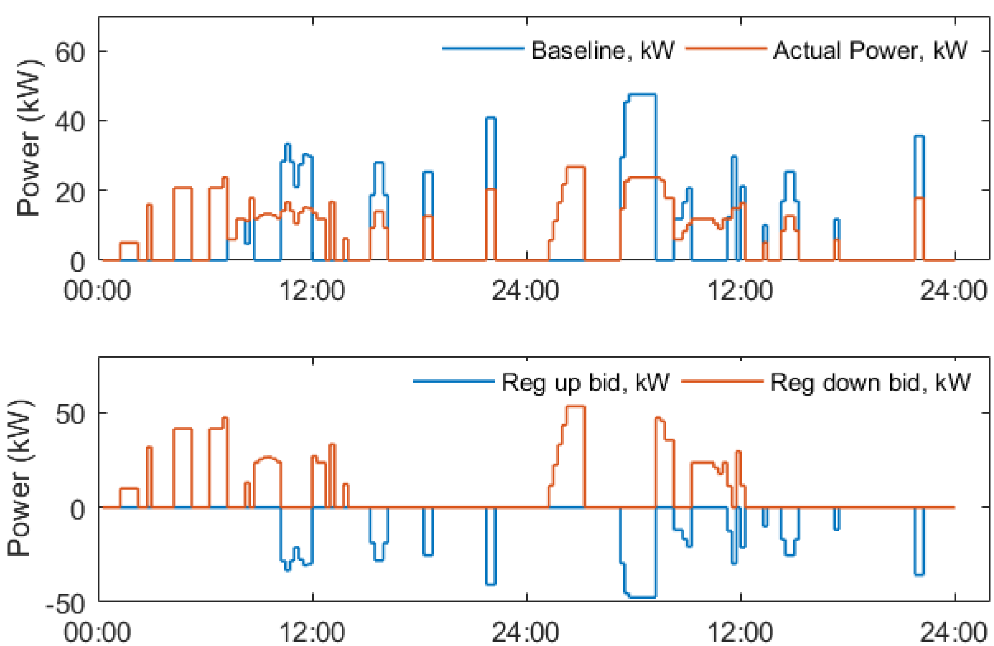
Figure 47: Example Load Profile for Two Days of Ancillary Service Regulation Up and Down Market Participation



Source: Lawrence Berkeley National Laboratory

The details of the regulation market participation are shown in Figure 48, including the baseline power, actual EV load profile (upper), and the actual regulation up/down bids (lower).

Figure 48: Results of Regulation Market Participation



Source: Lawrence Berkeley National Laboratory

Note that in (a), the blue curve denotes the EV baseline load profile and the red curve is the actual EV power consumption curve. Using both curves in the optimization, energy consumption (kWh) was held constant, constrained by equations (17) and (18).

Note that the duration of each regulation commitment was assumed to be 15 minutes in the optimization, within which the actual regulation signals are dispatched every 4 seconds. A 15-minute interval was also considered as the finest resolution for EV control. In addition, both regulation up and regulation down bids were allowed in the same time periods. Due to the assumption about the regulation up/down utilization rates, the regulation up/down bids were called partially, and the adjusted EV power consumption was reflected on as the differences between the baseline (blue) and the actual load profile (red) in Figure 48 (upper).

The monthly revenue results (Table 12) were collected by simulating EV management strategies for each month from January 2015 to December 2016.

Table 12: Monthly Revenue from the Regulation Market

Year	Month	Revenue	Year	Month	Revenue
2015	1	$90.38	2016	1	$74.53
2015	2	$66.42	2016	2	$66.33
2015	3	$73.88	2016	3	$90.37
2015	4	$95.73	2016	4	$71.75
2015	5	$78.09	2016	5	$68.62
2015	6	$67.75	2016	6	$95.70
2015	7	$76.57	2016	7	$69.22
2015	8	$68.51	2016	8	$77.28
2015	9	$78.16	2016	9	$61.50
2015	10	$80.48	2016	10	$78.24
2015	11	$63.24	2016	11	$79.70
2015	12	$98.11	2016	12	$115.14

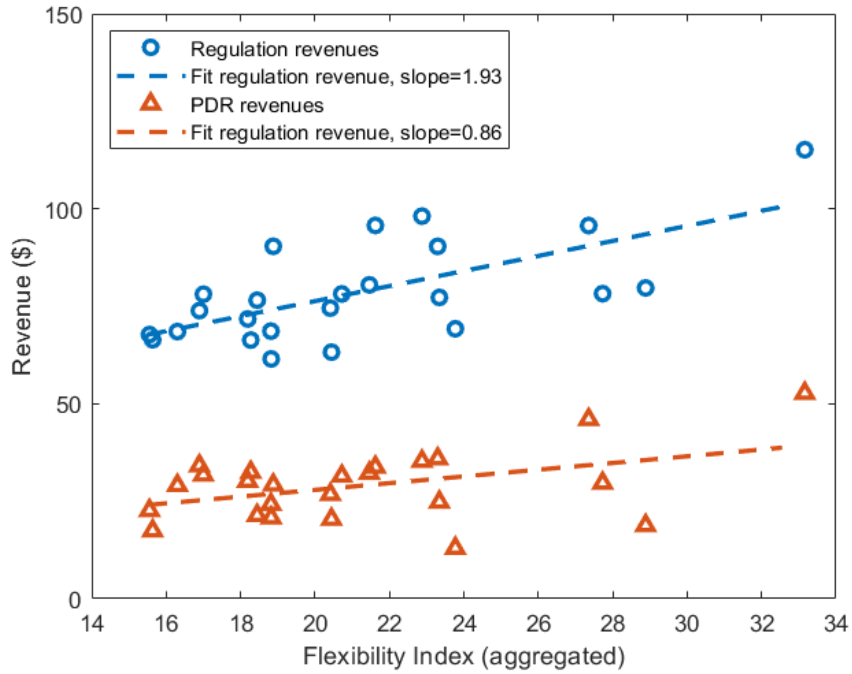
Source: Lawrence Berkeley National Laboratory

The highest monthly revenue was $115 in December 2016 and the lowest revenue was $78 in September 2016. The relationship between monthly regulation revenue and EV charging flexibility at the AlCoPark Garage is shown in Figure 49. To represent the monthly average distance between the upper and lower boundaries of the virtual battery, the flexibility index of the aggregated EVs is defined as:

$$f_{agg} = \frac{\sum_{d \in D} \sum_{t \in T} (E^{+}(t) - E^{-}(t))}{D \cdot T} \tag{35}$$

As indicated in Figure 49, the ability to generate profits in regulation markets was positively correlated with the flexibility index of the aggregated virtual battery, with a correlation coefficient of 0.667.

Figure 49: Monthly Profits versus Flexibility Index



Source: Lawrence Berkeley National Laboratory

Proxy Demand Resource Market Participation

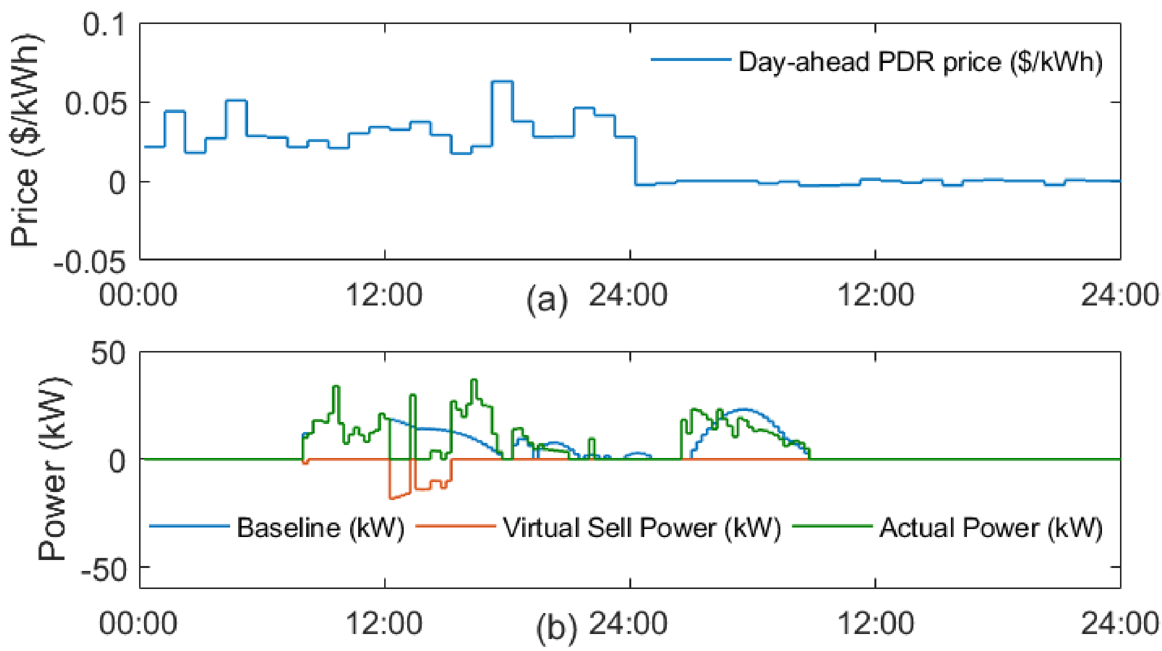
Problem 5 was addressed to simulate PDR market participation. CAISO requires participants to have at least a one-hour commitment into the PDR market. One-hour PDR market commitments were modeled with the constraints represented in equations (28) – (32). As shown in Figure 50 (lower), the green curve indicates the actual EV power consumption profile, while the red curve represents the virtual sell power of the aggregated EVs given price signals from the PDR market. The total energy consumption value following the actual power consumption profile should be equal to the one that follows the baseline profile generated by problem 2. In addition, problem 5 models the opportunities of the EVs to participate in the PDR market as discrete options, that is, the EV aggregator does not have to stay in the market for the entire day and can plan to step out of market when the PDR prices are not optimal.

The actual monthly revenues from PDR markets are illustrated by the red triangles in Figure 49, where the varying flexibilities of EV fleets to generate profits from PDR markets are shown. Note the consecutive commitment constraint is set to 1 hour for the PDR market optimizations.

Demand Bidding Program Participation

The modeling approaches for the PDR market integration were similar to those for the DBP market; however, there were different requirements for commitments in the DBP market. For instance, participation in the DBP market only occurs when the DBP events are issued by the program facilitator, PG&E, while hourly price signals in the PDR market were available daily. In PG&E's DBP program, $0.5 per kW is credited to commercial customers when they reduce their demand during DBP events. It was assumed in this analysis that the threshold to participate was greater than or equal to 10 kW and each commitment had to have a duration at least two consecutive hours. The simulation results for the DBP market participation is shown in Table 13.

Figure 50: Results of Proxy Demand Resource Market Participation



Source: Lawrence Berkeley National Laboratory

Table 13: Monthly Revenues from the Demand Bidding Program Market

Year	Month	Event #	Revenue
2016	6	5	$16
2016	7	6	$10
2016	8	2	$0
2016	9	1	$0

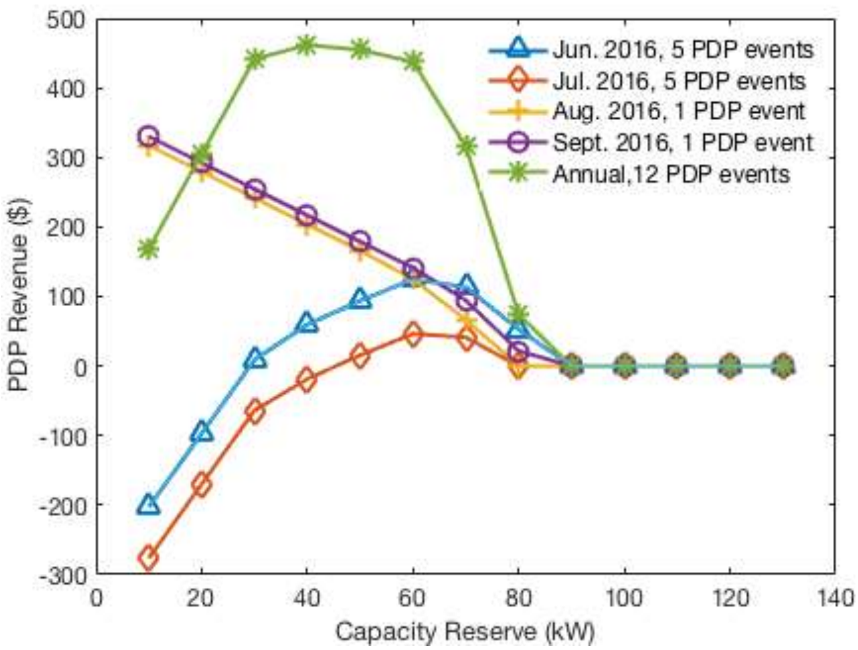
Source: Lawrence Berkeley National Laboratory

Due to the two-hour commitment constraint, the existing EV resources were not qualified to participate in all of the DBP events in 2016. Thus, the profit-generating capacity for EVs is not as high as for the regulation market, considering the limits of the fleet size and V1G power and flexibility.

Peak-day Pricing Program Participation

Participating the PDP program, the annual electric bill savings were expected to improve as the monthly peak demand and part-peak demand were partially protected by the capacity reserve level (CRL), which was required for PDP program enrollment. Specifically, as modeled by equations (10) – (12), the monthly peaks above the CRL received PDP credits, while the energy usage not protected by CRL was billed with a fixed PDP rate. PDP events were only issued during summers, and only peak and part-peak demands were considered. The monthly PDP benefit was calculated as $R_{PDP}^{p} + R_{PDP}^{pp} - C_{PDP}$. As shown in Figure 51, PDP benefits for summer months in the year of 2016 were computed with varying CRLs. For months with only one PDP event (August and September), PDP credits dominated the total benefit, which decreased as the CRL increased. In contrast, the event energy charge became dominant in months with more PDP events since there was less unprotected energy usage as the CRL increased between 10 kW and 60 kW. As CRL increased to greater than 60 kW, the month benefits decreased because of the weaker protection by CRL. In addition, the annual total PDP benefit varied with the CRL with the optimal CRL value close to 40 kW.

Figure 51: Impact of Capacity Reserve on Peak-day Pricing Benefits



Source: Lawrence Berkeley National Laboratory

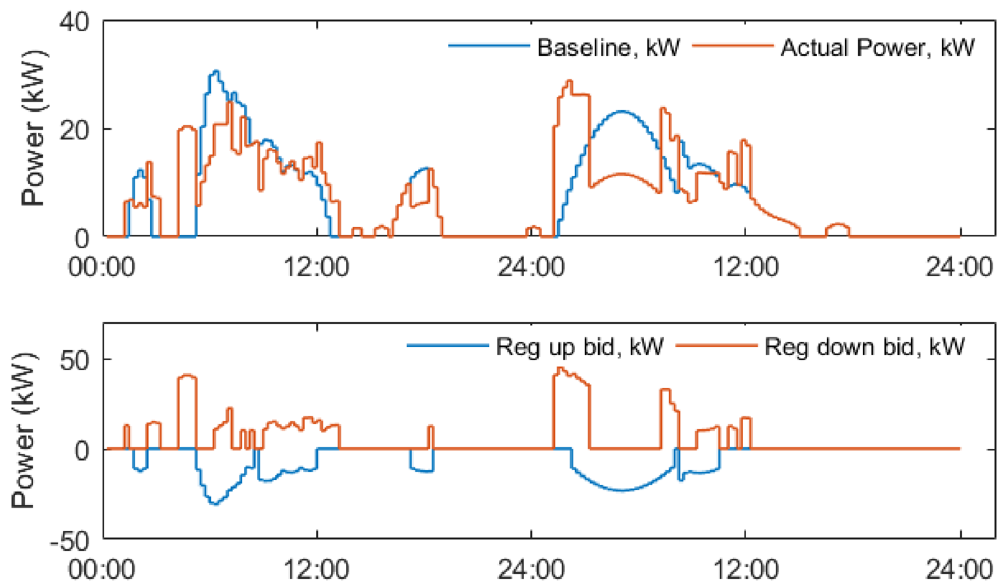
Discussion

This section discusses the impacts of different factors on the revenue-generating capability of the EV fleet, including the freedom of baseline power profile selection, flexibility of individual EVs, and market participation threshold. Simulation results indicate that proper tuning of these factors can lead to significant improvements in revenue generation.

Impact of Baseline Calculation

As opposed to the regulation simulation described above where baseline charging power was a decision variable, here the charging profiles obtained by solving problem 2 were used as baselines. As shown in Figure 52, the actual power (red) generally follows the baseline power profile (blue), unlike what is seen in Figure 48. However, the capability of the smart charging program was limited in exploring more space to generate revenues from regulation markets. The monthly revenue from regulation in June, 2016 was reduced from \$95 to \$36. Thus, with a preset baseline power profile, the flexibility was limited as well as the revenue-generating capability.

Figure 52: Fixed Baseline Case



Source: Lawrence Berkeley National Laboratory

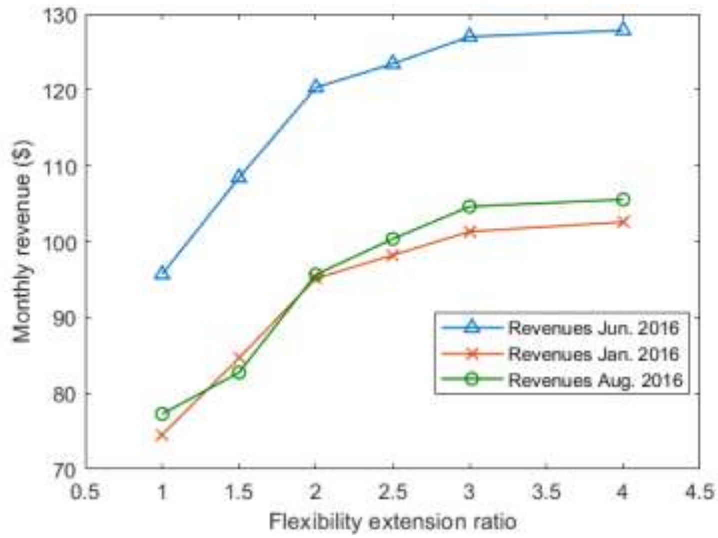
Impact of Flexibility on Regulation Revenue

To evaluate the impact of individual vehicle charging flexibility on regulation market revenues, the total connected duration of each EV was increased by multiple ratios to simulate different degrees of EV connected time flexibilities. For the months shown in Figure 53 (January, June, and August of 2016), revenues increased rapidly as the ratio of connected time to charging time increased from 1 to 2.5. However, as the ratio increased beyond 2.5, the total monthly revenue gradually plateaued. Note that in the simulation, two days was the maximum connected duration for each EV. Thus, within the given time period, limitations exist for revenue improvement by extending EV connected duration flexibility. However, for real-world operations, it will be beneficial for an EV fleet manager to maximize each EV's connected duration flexibility by having it either connect earlier or disconnect later.

Impact of Minimum Participation Threshold

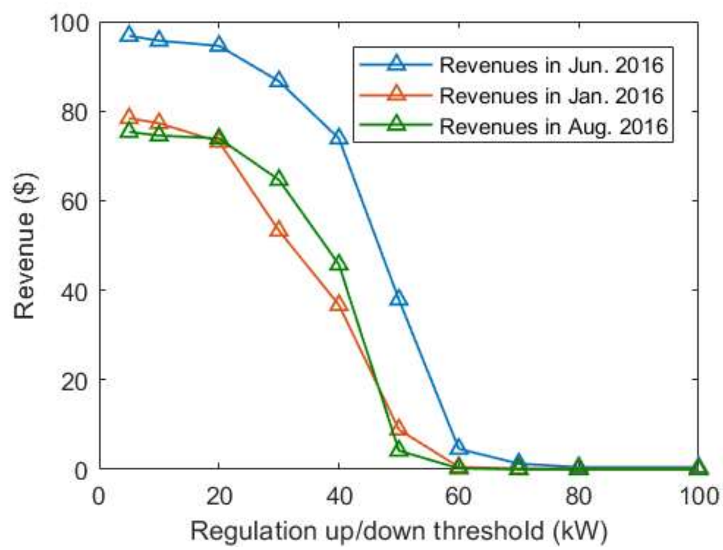
In the market participation simulations presented above, the minimum threshold to participate was 10 kW, which was appropriate for the size of the EV fleet in this study. Simulations to investigate the impact of varying threshold values on revenue is presented here. As the threshold value increases in Figure 54, the initial revenue drop is small, however, revenue sharply decreases as the threshold increases from 20 kW to 60 kW, indicating most of the commitments failed to satisfy the constraints defined by equation (19) and (20) because the required power adjustments exceeded the capacity of the EV fleet.

Figure 53: Impact of Flexibility



Source: Lawrence Berkeley National Laboratory

Figure 54: Impact of Minimum Participation Threshold



Source: Lawrence Berkeley National Laboratory

Smart Charging and Market Participation Summary

Flexibility in scheduling the charging of individual fleet EVs leads to greater revenue in all demand response and electric grid market participation. For example, monthly regulation revenue was approximately doubled when the fleet EV charging baseline was controlled rather than uncontrolled. One of the most critical aspects of smart charging control is the ratio of the time an EV is connected to a charging station port and the time the EV is actively charging. The simulations performed in this study show that the ratio does not have to exceed roughly 2-3 to maximize revenue from regulation ancillary services market participation. This is a good finding for EV fleet owners or aggregators since it means that, with regards to maximizing regulation revenue, participating EVs do not have to be left connected to charging stations for very long periods after charging is complete, which will allow a greater utilization of charging equipment. Wholesale demand response and ancillary services markets have minimum levels of participation. This study shows that, for the EV fleet simulated, any threshold below 40 kW corresponds to maximum market participation revenues. Either threshold requirements have to be kept low or larger aggregations of fleet EVs will be needed for profitable market participation with higher thresholds.

CHAPTER 6: Conclusions, Future Work, and Challenges

Conclusions and Future Work

This project successfully demonstrated a set of smart charging strategies at an Alameda County public parking garage, that also houses the county's primary fleet vehicle facility, to manage charging station loads and reduce utility costs. Alameda County was so pleased with the outcomes of the project that they paid a two-year contract to continue operation of the fleet management smart charging system at the AlcoPark Garage. Another significant success of this project comes in the form of technology transfer where a major charging service provider, ChargePoint, purchased project partner Kisensum in order to incorporate the technology developed in this project into their commercial product offerings because of the value that it brings to their fleet and commercial customers.

A key feature of every smart charging control strategy presented here is that each EV whose charging time was adjusted received the same full charge and charging power it would have received had the smart charging control not been implemented.

For public EVs, the managed charging strategies reduced daily peak energy demand by 7.0 kW. During the original peak period from 8 a.m. to 11 a.m., the peak demand was reduced from 24.2 kW to 10.0 kW. The total charging power of all the public charging stations decreased by 12.0 kW, which is about 26.7 percent of the original uncontrolled peak demand. For fleet EVs, the peak demand during the on- and mid-peak periods was reduced by 10.7 kW and 13.3 kW separately in one week during the summer period. For DCFC charging, the maximum power reduction was 20 kW, nearly half of the DCFC charging power in the normal mode. The median value of the power reductions was 4.3 kW, which is equal to the kW shed from one active charging session.

During the testing of charging control for public EVs, there was an issue of charging power interruption during the charging session when the charging power setting was less than 1.5 kW. Frequent power interruptions may lead to charging sessions ending earlier than expected, which can cause "range anxiety" for drivers due to the unexpected loss of charging. Regarding the charging control of the DC fast charger, the researchers observed that the performance of this control strategy for managing the power spike from DC fast charging in a short period varies along with the number of the active charging sessions on the selected stations. Each active charging session can easily contribute about 4.5 kW of power reduction to offset the power spike.

The researchers quantified the potential of the aggregated fleet EVs in participating multiple demand response products in the California retail and wholesale electricity markets. Comprehensive evaluation models were developed for the integration of EVs into various demand response products, analyzing the revenues and investigating the impact of multiple factors on the revenue-generating capabilities. For future work, researchers will explore the online strategies within these real-world market contexts as potential implementable solutions.

Challenges

Public Charging Challenges

For the public charging control, only 4.6 percent of the public charging sessions were controlled during the pilot study period. Educational materials such as flyers and workshops are needed to make public drivers aware of the effects of smart charging control on utility cost and on the environment. It is also important to guarantee that customers' requests for charging energy are met by the end of the charging session without any compromise. Lastly, there are tradeoffs between lower charging rates and longer parked duration versus higher charging rates and shorter parked duration.

Difficulties were encountered in recruiting and maintaining volunteers for study participation. Future studies of a similar nature would benefit from more knowledge and information on incentivizing human behavior with respect to public participation recruitment and retention.

Fleet Management and Vehicle State of Charge Challenges

Having a greater number of fleet EVs than charging stations limits the cost saving potential from the smart charging control. In addition, fleet staff cannot rotate vehicles to available charging stations outside of garage operating hours (7 a.m.-7 p.m.). Simple scheduling works well for fleet charging, but may vary depending on fleet vehicle activity patterns.

Given the current limitations, a better coordinated fleet charging system would also improve performance and reduce utility costs by linking fleet vehicle trip management with the smart charging control. Moreover, the fleet EV dashboard could be fully used to improve the fleet EV charging control.

Fast Charging Challenges

Researchers observed that the performance of the control strategy for managing the power spike from DCFC charging in a short period varies with the number of the active charging sessions on the selected stations. Some success is achieved in decreasing demand during DCFC sessions by synching control of a large number of Level 2 fleet stations. However, given the increasing number of DCFC sessions, there is still a high likelihood of not having a large number of Level 2 fleet stations when a DCFC session is on. To address this issue, fixed battery storage can be integrated with the DCFC charging station by optimizing the charging and discharging of the battery and DCFC session along with other charging sessions.

LIST OF ACRONYMS

Term	Definition
API	Application program interface
CAISO	California Independent System Operator
CRL	Capacity reserve level
DBP	Demand Bidding Program
DCFC	Direct current fast charging
DR	Demand response
EPIC	Electric Program Investment Charge
EV	Electric vehicle
EVSE	Electric vehicle supply equipment
JSON	JavaScript Object Notation
kW	Kilowatt
kWh	Kilowatt-hour
LBNL	Lawrence Berkeley National Laboratory
PDP	Peak-day pricing
PDR	Proxy demand resource
PHEV	Plug-in hybrid electric vehicle
PG&E	Pacific Gas and Electric Company
SMS	Short Message Service
SOC	State of charge
TOU	Time-of-Use
USDOE	United States Department of Energy
VGI	Vehicle-grid integration
V2G	Vehicle-to-grid

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